Abstract: Climate change can impact the yield and water footprint of crops. Therefore, assessing such impacts carries great significance for regional water and food security. This study validated and verified the variety parameters of winter wheat for the Decision Support System for Agrotechnology Transfer (DSSAT) model, using the long-term (1993–2013) growth and yield data observed from six agricultural experiment stations in the Haihe River Basin (HRB), China. The growth process was simulated under three representative concentration pathways (RCPs), named RCP2.6, RCP4.5, and RCP8.5—climate scenarios driven by the HadGEM2-ES model. The variety parameters of winter wheat showed high accuracy in the simulation of the anthesis and maturity dates, and could be used for long-term prediction of the growth process. The trends of climate change had positive impacts on the water footprint of winter wheat but adverse impacts on the yield. The growing period was shortened by 3.6 days, 4.7 days, and 5.0 days per decade in the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively, due to the rapid accumulation of heat. The yield would be increased in lower emissions scenarios (17% in RCP2.6), but decreased in high-emissions scenarios due to high temperatures, which may restrict the growth of wheat. The water footprint was decreased by 10%, 11%, and 13% in the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively, indicating that the water-use efficiency could be improved in the future. The results showed broad application prospects of the DSSAT model in simulating the response of crop growth to climate change.

Keywords: variety parameters; DSSAT model; growth process; RCPs scenarios

1. Introduction

Climate change poses a huge threat to the world’s water and food security. According to the sixth assessment report (AR6) of the Intergovernmental Panel on Climate Change (IPCC), the global surface temperature was 1.09 °C higher in 2011–2020 than in 1850–1900, and the global surface in each of the last four decades has been successively warmer than any decade since 1850 [1,2]. Agriculture has been significantly affected by climate change [3–5]. The rising temperature has affected photosynthesis and transpiration, the growing period, and production [6–9]. In addition, the increase in temperature has affected the hydrological process and brought changes in evapotranspiration and precipitation [10–12]. The water footprint can be recognized as a comprehensive indicator to evaluate the sustainable utilization of agricultural water under climate change, which reflects water volumes, water sources, and the amount of water required to eliminate agricultural water pollution [13–16]. Assessing the impact of climate change on the yield and water footprint of winter wheat could improve our understanding of the vulnerability
of agricultural water systems to climate change, and also provide advice with respect to protecting water and food security in case of future climate change [17,18].

The impact of climate change on crop yield and related water footprint has been assessed around the world. [19]. Prior studies have assessed the impact of climate change on crops based on observed historical data, showing direct changes in the yield and crop growth. Lobell and Asner noted that yields of corn and soybeans tended to decrease by roughly 17% for each 1 °C increase in temperature in the growing season in the United States [20]. The sensitivity analysis provides an important approach to the assessment of the impact of climate change on crops [21–23]. A series of meteorological factors are sensitive to crop evapotranspiration, such as temperature [24–26], vapor pressure [27,28], and other climate factors [29]. These studies improve our understanding of the effects of climate change on crops. However, the changes in crop growth and yield and the related water footprint in future climate scenarios are still uncertain.

Crop models are powerful tools to predict crop growth and yield under climate change scenarios [30,31]. A number of models—such as Crop Environment Resources Synthesis (CERES), Decision Support System for Agrotechnology Transfer (DSSAT), Agriculture Production Systems Simulator (APSIM), World Food Studies (WOFOST), and Soil–Water–Atmosphere–Plant (SWAP) [32–35]—are coupled with some climate scenarios to simulate crop growth and yield. Yano et al., (2007) pointed out that the rising temperature accelerated crop development and shortened the growing period by 24 days for wheat, and the irrigation amounts would increase by 10–30% according to the CGCM2 data in a Mediterranean environment [36]. Gao et al., indicated that the crop water requirement increased by 11.6–86.2% under the impacts of climate change in the multiple cropping areas in North China [37]. Garofalo et al., demonstrated that the yield would increase by 9% while the water consumption remained stable in a continental area of Europe [38]. Boonwichai et al., pointed out the rising temperature would increase the water requirements of rice in Thailand [39]. Fu and Zhao simulated the yield and water-use efficiency of wheat under different warming rates [40].

Prior studies have made significant progress in simulating the crop growth and yield and clarifying the response of crops to climate change in many areas, using crop models [41–43]. However, for some especially climate-sensitive areas (e.g., temperate semi-humid and semi-arid monsoon climate areas), studies using crop models coupled with scenarios of representative concentration pathways (RCPs) are still scarce. In addition, many crop models simulate the crop growth using 2–3-year observed data (especially the genetic parameters) in the process of model calibration and validation due to a lack of long-term historical data. The short-term observed data would be not enough for estimating long-term climate change processes [44–46].

The Haihe River Basin (HRB) is a political, economic, and cultural center of China with 146 million inhabitants. It is also a major grain-producing area, with a total yield of 24.7 million tons of wheat. The HRB is located in the temperate semi-humid and semi-arid monsoon climate zones. The per capita water resources are 210 m³—less than 1/10 of the national average. Water resources and crop growth are sensitive to climate change in this typical water-deficient region [47–49]. Therefore, this paper studies the case of the HRB, and aims to (1) determine proper variety parameters of winter wheat for the simulation of long-term climate conditions, (2) assess the yield and water footprint of winter wheat in future RCP scenarios, and (3) clarify the response of yield and water footprint to climate change.

2. Methodology and Data

2.1. Study Areas

The HRB is located between 112° E–120° E and 35° N–43° N, with a drainage area of 318,200 km². It encompasses Beijing, Tianjin, and 23 other large- and medium-sized cities. The basin is located in a continental monsoon climate zone with annual mean temperatures of −4.9–15 °C and annual precipitation ranging from 380 mm to 580 mm. The precipitation
in the monsoon season (June–September) generally accounts for 70–85% of the annual total precipitation. This study collected data on soil, genetic parameters, weather, and field management from six agricultural experimental sites, i.e., Dingzhou and Luancheng in Shijiazhuang (SJZ), Miyun and Tongxian in Beijing (BJ), and Baodi and Jinghai in Tianjin (TJ). The locations of the HRB, the weather stations, and the experimental sites are shown in Figure 1.

Figure 1. Locations of the study areas and agricultural experiment stations.

2.2. Data Inputs, Calibration, and Validation of the DSSAT Model

The inputs of the DSSAT model include data on soil, genetic parameters, weather, and field management. The genetic parameters of wheat were calibrated and validated using the “trial and error” method, based on the historical data observed from 1993 to 2013 at six agricultural experimental sites. The data for crop growth were obtained from the China Meteorological Administration (Beijing, China) [50], which only offered data from 1993 to 2013, and did not provide data after 2014. The observed data in the periods 2005–2013 and 1993–2004 were used to calibrate and validate the model, respectively. The wheat was cultivated in rows, with spacing of 20 cm. There were 240 plants of winter wheat per square meter. Ammonium bicarbonate (NH₄HCO₃) was mostly applied as the fertilizer. In the model, the crops were fertilized twice in the growing period, with 86 kg of pure nitrogen per hectare each time, and were irrigated four times, with 60 mm of water each time, during the periods of wintering (12/01), stem elongation (3/29), heading (4/20), and grain filling (5/15) [51,52]. Phosphorus and potassium were not simulated in the model.

The soil data were obtained from the Chinese Soil Database [53,54]. The dominant soil type was “Loess soil,” with a texture of sandy clay loam. The diameter, nutrients, and physical and chemical properties of the soil particles are listed in Table 1 below.
Table 1. Typical characteristics of soil in HRB.

| Soil Type | Relative Thickness (cm) | The Percentage of Soil Size | Nutrients, and Physical and Chemical Properties |
|-----------|-------------------------|-----------------------------|------------------------------------------------|
|           | 2–0.02 mm mm | 0.02–0.002 mm mm | <0.002 mm mm | Cation exchange capacity: 11.5 cmol/ (+); organic matter: 8.3 g/kg; total nitrogen: 0.59 g/kg; total phosphorus: 0.46 g/kg; total potassium: 17.5 g/kg; water extraction pH: 8.2. |
| Loess     | 18          | 61.2          | 23.55      | 15.3          |
|           | 23          | 62.79         | 23.18      | 15.1          |
|           | 76          | 56.43         | 25.72      | 17.9          |
|           | 33          | 56.13         | 26.93      | 16.9          |

The genetic parameters of winter wheat include ecological parameters and variety parameters. The default “USWH01” was used for the ecological parameters. The key variety parameters used in the model are listed in Table 2 [51,55,56]. The variety parameters were manually calibrated and validated based on the observed data from 2005–2013 and 1993–2004, respectively. The growth data were obtained from 6 agricultural experimental sites. The calibrated and validated results are shown in Table 2.

Table 2. The variety parameters of winter wheat.

| Parameters | Explanations [32] | Shijiazhuang | Beijing | Tianjin |
|------------|-------------------|--------------|---------|---------|
| PIV        | Vernalization sensitivity coefficient, days | 35           | 35      | 15      |
| PID        | Photoperiod sensitivity coefficient, %h   | 75           | 65      | 65      |
| P5         | Thermal time from the onset of linear filling to maturity, °C.days | 550          | 550     | 550     |
| G1         | Kernel number per unit stem + spike weight at anthesis, numbers/g | 17           | 15      | 15      |
| G2         | Standard kernel size under optimal conditions, mg | 32           | 30      | 30      |
| G3         | Standard, non-stressed dry weight of a single tiller at maturity, g | 1.4          | 1.4     | 1.1     |
| PHINT      | Thermal time between the appearance of leaf tips, °C.days | 70           | 70      | 70      |

The weather data were obtained from the China Meteorological Administration [50], including daily maximum and minimum air temperatures, wind speed at 2 m height, relative humidity, and daily sunshine duration. The data were proofread and corrected and the missing data were interpolated. The weather data in average years in the HRB are shown in Table 3.

Table 3. The average weather data in the study areas.

|                | Precipitation (mm) | Min. Temperature (°C) | Max. Temperature (°C) | Wind Speed (m/s) | Relative Humidity (%) | Sunshine Hours (h) |
|----------------|--------------------|-----------------------|-----------------------|------------------|-----------------------|-------------------|
| Shijiazhuang   | 510                | 9.9                   | 19.5                  | 1.5              | 57.0                  | 2135              |
| Beijing        | 496                | 8.5                   | 18.5                  | 2.3              | 52.7                  | 2425              |
| Tianjin        | 527                | 9.2                   | 18.1                  | 1.2              | 59.1                  | 2244              |

In the DSSAT model, the infiltration and soil water dynamics were simulated based on the equation provided by the Soil Conservation Service of America (Washington, DC, USA) and the one-dimensional water balance model developed by Ritchie [57] (pp. 41–54). The evapotranspiration was simulated daily using the Penman–Monteith method in FAO-56. The life cycle of winter wheat was divided into several phases, and the development rate was controlled by accumulated heat quantified by growing degree-days (GDD). The yields
were simulated based on the potential seed weight and kernel numbers derived from genetic parameters and the conversion of cumulated carbohydrates.

The water consumption of winter wheat was calculated by summing up the simulated daily evapotranspiration during the growth period. The water footprints of winter wheat were calculated by dividing the amount of consumed water by the simulated crop yield \[47,58\].

2.3. Model Evaluation

The performance of the model was evaluated by a number of indicators named “the normalized root mean square, NRMSE”, “the coefficient of residual mass, CRM”, “the coefficient of determination for linear relationship, \(r^2\)”, and “the index of agreement, \(d\)”.

The NRMSE was used to measure the relative difference between the simulated and measured values \[59\]. The results were graded as “excellent”, “good”, “moderate”, or “poor”, corresponding to an NRMSE of “\(\leq 10\%\)”, “10–20\%”, “20–30\%”, or “\(\geq 30\%\)”, respectively.

\[
NRMSE = \sqrt{\frac{\sum_{i=1}^{n} (S_i - R_i)^2}{n}} \times \frac{100}{R} \tag{1}
\]

where NRMSE is the normalized root-mean-square error, \(n\) is the number of samples, \(S_i\) is the simulated value, \(R_i\) is the observed value, and \(R\) is the average of observed values.

The CRM is an indicator of whether the model predictions tend to over- or underestimate the observed data \[60\]. A negative or positive CRM value indicates a tendency of the model toward over- or underestimation, respectively.

\[
CRM = 1 - \frac{\sum_{i=1}^{n} S_i}{\sum_{i=1}^{n} R_i} \tag{2}
\]

where CRM is the coefficient of residual mass.

The index of agreement (\(d\)) was used to verify the consistency between the simulated and measured values.

\[
d = 1 - \frac{\sum_{i=1}^{n} (S_i - R_i)^2}{\sum_{i=1}^{n} (|S_i - R| + |R_i - R|)^2} \tag{3}
\]

where \(d\) is the index of agreement. We considered the index of agreement between measured and simulated values to be “excellent” when \(d > 0.9\), “good” when \(0.8 \leq d < 0.9\), “moderate” when \(0.7 \leq d < 0.8\), and “poor” when \(d < 0.7\).

2.4. Simulation in Future Climate Scenarios

The IPCC distinguishes four RCPs (RCP2.6, 4.5, 6, and 8.5) based on radiative forcing levels by 2100 (from 2.6 to 8.5 W/m\(^2\)) \[61\]. RCP2.6, RCP4.5, and RCP8.5 were employed in this study, representing pathways below the 10th percentile, moderate, and below the 90th percentile of the reference emissions range, respectively \[62\]. The future climate data for the RCP2.6, RCP4.5, and RCP8.5 scenarios were generated driven by the HadGEM2-ES model developed by the Hadley Centre of the UK Met Office (Exeter, UK). The generated data were scaled down to the HRB by a monthly scaling-down method.

The growth process and yield in the future were simulated by the DSSAT model coupled with RCP scenarios by creating corresponding new weather stations to store the generated weather data. The planting time of winter wheat in the RCP scenarios was assumed to be the same in the simulation model.

3. Results

3.1. Simulation of Winter Wheat Growth and Yield Using the DSSAT Model

(1) Anthesis dates

The regression between the observed and simulated values of anthesis dates was conducted using the 1:1 line, and the results are shown in Figure 2; \(r^2\) explained most of the
deviations between the simulated and measured values during calibration and validation for Beijing and Tianjin, with results ranging from 0.83 to 0.91, while for Shijiazhuang, the $r^2$ was poor at 0.40.

Figure 2. Calibration and validation results of anthesis dates. (a–c) are calibration results for Beijing, Shijiazhuang, and Tianjin, respectively; (d–f) are validation results for Beijing, Shijiazhuang, and Tianjin, respectively.

The calibration and validation results for anthesis dates are shown in Table 4. The simulated mean values were 211–223 days after planting (DAP)—1–4 days later than the observed values. The NRMSE shows an “excellent” performance of the model, with values ranging from 1.9% to 2.3%. The CRM shows that the anthesis date estimated was later than the observed dates, with a range from $-0.023$ to $-0.004$. The values of “$r$” show that the simulated and observed days for anthesis were significantly correlated ($p < 0.001$).

(2) Maturity dates

The calibration and validation results of maturity dates are shown in Figure 3. Most of the deviations between the simulated and measured values could be explained by $r^2$, with values ranging from 0.65 to 0.91, except for the validation for Shijiazhuang (0.42). The calibration and validation results for maturity dates are shown in Table 5. The simulated mean was 247–255 days after planting (DAP)—close to the observed numbers for calibration and validation, with a range from 3 days earlier to 2 days later. The NRMSE shows an “excellent” performance of the model, with values ranging from 1.0% to 1.7%. The CRM ranging from $-0.008$ to $0.011$ also shows that the simulated values were close to the observed ones. The negative or positive values indicate that the simulated values were underestimated or overestimated compared with the observed ones, respectively. The values of “$r$” show that the simulated and observed days for maturity were significantly correlated ($p < 0.001$).
Table 4. Calibration and validation results of the DSSAT model for anthesis dates.

| Parameters        | Shijiazhuang | Beijing  | Tianjin |
|-------------------|--------------|----------|---------|
|                   | Obs          | Sim      | Obs     | Sim     | Obs     | Sim    |
| Mean              | 214          | 218      | 223     | 224     | 220     | 223    |
| Standard deviation| 5.1          | 4.8      | 7       | 9       | 7       | 8      |
| Minimum           | 203          | 208      | 210     | 211     | 206     | 210    |
| Maximum           | 223          | 227      | 235     | 238     | 230     | 239    |
| Data number       | 18           | 18       | 18      |          |         |        |
| r                 | 0.85 ***     | 0.96 *** | 0.91 ***|          |         |        |
| NRMSE, %          | 2.3          | 1.2      | 1.9     |          |         |        |
| CRM               | −0.019       | −0.004   | −0.013  |          |         |        |
| d                 | 0.21         | 0.03     | 0.09    |          |         |        |

Validation

| Parameters        | Shijiazhuang | Beijing  | Tianjin |
|-------------------|--------------|----------|---------|
|                   | Obs          | Sim      | Obs     | Sim     | Obs     | Sim    |
| Mean              | 211          | 216      | 222     | 225     | 218     | 222    |
| Standard deviation| 5.2          | 5.3      | 7       | 8       | 7       | 6      |
| Minimum           | 196          | 206      | 210     | 210     | 206     | 210    |
| Maximum           | 218          | 225      | 234     | 239     | 231     | 233    |
| Data number       | 22           | 21       | 24      |          |         |        |
| r                 | 0.71 ***     | 0.93 *** | 0.92 ***|          |         |        |
| nRMSE, %          | 3            | 1.9      | 1.8     |          |         |        |
| CRM               | −0.023       | −0.015   | −0.015  |          |         |        |
| d                 | 0.31         | 0.09     | 0.10    |          |         |        |

Notes: *** represents significance levels of 0.001; “Obs” means observation values; “Sim” means simulation values.

Figure 3. Calibration and validation results of the DSSAT model for maturity. (a–c) are calibration results for Beijing, Shijiazhuang, and Tianjin, respectively; (d–f) are validation results for Beijing, Shijiazhuang, and Tianjin, respectively.
Table 5. Calibration and validation results of the DSSAT model for maturity dates.

| Parameters | Shijiazhuang | Beijing | Tianjin |
|------------|--------------|---------|---------|
|            | Obs | Sim | Obs | Sim | Obs | Sim |
| **Calibration** |      |      |      |      |      |      |
| Mean       | 250 | 247 | 255 | 255 | 253 | 253 |
| Standard deviation | 3.6 | 4.3 | 6.4 | 8.2 | 7.8 | 7.3 |
| Minimum   | 244 | 240 | 243 | 240 | 237 | 240 |
| Maximum   | 258 | 257 | 265 | 267 | 262 | 268 |
| Data number | 17  | 17  | 18  |      |      |      |
| r         | 0.81*** | 0.97*** | 0.84*** |      |      |      |
| nRMSE, % | 1.4 | 1.0 | 1.7 |      |      |      |
| CRM       | 0.011 | 0.001 |      | −0.008 |      |      |
| **Validation** |      |      |      |      |      |      |
| Mean       | 248 | 247 | 251 | 253 | 252 | 253 |
| Standard deviation | 2.8 | 4.5 | 6.6 | 8.8 | 6.2 | 6.4 |
| Minimum   | 243 | 238 | 240 | 241 | 242 | 241 |
| Maximum   | 253 | 256 | 265 | 269 | 263 | 262 |
| Data number | 18  | 17  | 24  |      |      |      |
| r         | 0.65** | 0.92*** | 0.76*** |      |      |      |
| nRMSE, % | 1.4 | 1.7 | 1.7 |      |      |      |
| CRM       | 0.004 | −0.008 |      | −0.002 |      |      |

Notes: ** and *** represent significance levels of 0.01 and 0.001, respectively. "Obs" means observation values; "Sim" means simulation values.

(3) Yield of winter wheat

The calibration and validation results of yield are shown in Figure 4. The NRMSE shows a “good” performance in “Shijiazhuang”, “Beijing”, and “Tianjin”, with values of 12.5%, 18.8%, and 17.5%, respectively. The index of agreement “d” shows a moderate performance in “Shijiazhuang”, “Beijing”, and “Tianjin”, with values of 0.38, 0.53, and 0.41, respectively.

Figure 4. Calibration and validation results of yield for winter wheat. (a-c) are simulated yield for Shijiazhuang, Beijing, and Tianjin, respectively.

3.2. Prediction of Growth Process, Yield, and Water Footprint under RCP Scenarios

(1) Growing period

The growing periods of winter wheat were significantly shortened in the RCP2.6, RCP4.5, and RCP8.5 scenarios, as shown in Figure 5. By 2050, the growing period would be shortened by 13 days, 16 days, and 18 days compared to 2015 in the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively, meaning that the decrease was 3.6 days, 4.7 days, and 5.0 days per decade, respectively. The downward trends were more significant in Tianjin, with a decrease of 4.9 days, 5.7 days, and 6.6 days per decade in RCP2.6, RCP4.5, and RCP8.5, respectively.
(2) Crop yield

The simulation results of yields are shown in Figure 6. Although the yields increased in all climate scenarios, the increase was even greater in the low-emissions scenario of RCP2.6. By 2050, the yield would increase by 1.5 t/ha, 1.46 t/ha, and 1.39 t/ha compared to 2015, respectively. The ranges of increased yields were inhomogeneous in space. In Tianjin and Beijing, the yields increased more than those in Shijiazhuang, mainly because the starting yields in 2015 were lower in Tianjin and Beijing.

(3) Water consumption

The simulated results of water consumption during the growth process of winter wheat are shown in Figure 7. The volumes of water consumption increased in the lower emissions scenario (RCP2.6), but the trends were not significant in the RCP4.5 and RCP8.5 scenarios. These results may be related to the length of the growing period. In the RCP4.5 and RCP8.5 scenarios, the growing period was shortened by 16 and 18 days, respectively, according to the previous section of this study. From the perspective of daily water consumption in the growing period, the water consumption was increased in all scenarios.
(4) Water footprint
The simulated results for water footprint production are shown in Figure 8. The water footprints significantly decreased, indicating that the water-use efficiency would be improved—especially in high-emissions scenarios (RCP8.5). By 2030, the water footprint would decrease by 4%, 8%, and 6% in the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively. By 2050, the water footprint would decrease by 10%, 11%, and 13% in the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively. Water footprints decreased the most in Beijing in terms of space, by 14%, 23%, and 16% in the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively.

![Figure 8. The water footprint of wheat in the different RCP scenarios. (a–c) are water footprint for Shijiazhuang, Beijing, and Tianjin, respectively.](image)

4. Discussion
The calibrated and validated results of variety parameters were compared to others in the HRB, and are shown in Table 6. Du calibrated two varieties (“41,581” and “Kenong199”) at the Luancheng agricultural experimental station in Shijiazhuang [50]. The variety of winter wheat in this study was similar to “41,581”.

| Variety       | PIV | PID | P5   | G1  | G2   | G3   | PHINT |
|---------------|-----|-----|------|-----|------|------|-------|
| Current study | 35  | 75  | 550  | 17  | 32   | 1.4  | 70    |
| “41,581”      | 32.76 | 82.79 | 558.2 | 17.16 | 34.31 | 1.144 | 70    |
| “Kenong199”   | 39.22 | 59.13 | 656.3 | 17.55 | 37.77 | 1.933 | 70    |

The growing period decreased by 3.6 days, 4.7 days, and 5.0 days per decade in the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively, which were compared to others. Zhang et al., found that the growing period of winter wheat would be shortened by 0.84 days per decade in the combination model of BCCT63 and WOFOST [63]. Li et al., found that the growing period from sowing to ripening in the RCP8.5 climate scenario would be shortened by 4 days and 15 days in the periods 2010–2039 and 2040–2069, respectively [64]. The reason for the shorter time period in this study than in Li’s study was mainly because the observation point was at a higher latitude than Li’s, with a lower temperature and more pronounced monsoon climate—especially in Beijing and Tianjin. A few scholars indicated changes in the growing period based on historical data observed in the HRB. Ji et al., indicated that the heading and ripening dates were 4.6 days and 2.7 days earlier each decade, respectively, in 1983–2005 [65]. Yu et al., indicated that the growing period was shortened by 1.3 days per decade, and that the decreasing trend would be even faster in future climate scenarios [66]. The changes in the growing period in the RCP scenarios were related to the thermal time or so-called “growing degree-days (GDD)” [19,32]. As temperature rises, the GDD of winter wheat reaches the threshold in advance for maturity.

In Shijiazhuang, we found a relatively poor correlation ($r^2$) for the anthesis dates and maturity dates. This is also related to the accumulation of heat. Shijiazhuang is in the south
of the Haihe River Basin, and the temperature differences between spring and summer are smaller than in Beijing and Tianjin (in summer, the temperature is high in the whole basin, or even throughout China, while in the winter there is large difference between different latitudes). Hence, in Shijiazhuang the dates of anthesis (or maturity) are more centralized, as can also be seen in Figures 2 and 3. This may lead to a relatively poor correlation \((r^2)\) in anthesis (or maturity) dates in Shijiazhuang than in the other two regions.

The yields showed an increasing trend in future climate scenarios. Li believed that the yields in the RCP8.5 scenario would increase by 14.88% in the period 2040–2069 [64]. Meanwhile, in this study, the yield increased by 14.7% in the RCP8.5 scenario for Shijiazhuang, which is close to Li’s estimate. Yang et al., clarified that the actual yield of winter wheat in Ningjin (a city in southern Shijiazhuang) increased by 1.36 tons per decade in the period 1982–2018 [67], while in this study, it was 0.2–0.3 tons per decade, indicating that the increasing trend would slow down in the future. The yield would increase in future climate scenarios because the increasing temperature can boost photosynthesis and dry matter accumulation in winter wheat. Among them, the effects of low- and medium-emission conditions on the increase in winter wheat yield is higher than that of high-emission conditions, because in high-emission scenarios, a higher temperature may cause damage to the growing process of crops.

By 2050, the water footprints would decrease by 10%, 11%, and 13% in the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively, indicating that the water-use efficiency would be improved. The water footprint was influenced by two factors: the water consumption during the growing seasons, and the yield. The water consumption in the growing seasons of wheat was not significantly increased—especially in high-emission scenarios—because the growth days were significantly shortened, although the daily consumption of water did increase to a certain extent. Meanwhile, the yields were increased, according to the experimental results and above analysis.

Because of the lack of data on biomass, the accuracy of yield simulation was affected. In addition to the genetic kernel numbers and the weight of winter wheat, a portion of the yield was derived from the conversion of biomass. When photosynthesis declines, the protein and carbohydrates mobilized from vegetative tissue contribute to seed growth [32]. In the future, a few parameters (e.g., biomass) should be monitored to improve the accuracy of yield simulation. In addition to climate change, the water footprint of winter wheat was also influenced by such factors as technological innovation, and their effects would be greater than the impact of climate change [68–70]. In the future, the influence of multiple factors on crop yield and water footprint should be considered.

5. Conclusions

In this study, the variety parameters of winter wheat were validated and verified with the DSSAT model using the long-term (1993–2013) growth and yield data observed from six agricultural experimental stations in the HRB, China. The growth processes were simulated by the DSSAT model coupled with RCP scenarios (RCP2.6, RCP4.5, and RCP8.5) driven by the HadGEM2-ES model, so as to understand the impacts of climate change on the yield and water footprint of winter wheat. The calibrated and validated variety parameters of winter wheat had high accuracy in simulating the anthesis and maturity dates, and could be used for the prediction of future winter wheat growth processes in the HRB. The results showed that future climate scenarios could speed up the growth process and improve the yield. The growing periods were significantly shortened, by 3.6 days, 4.7 days, and 5.0 days per decade in the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively, due to the rapid accumulation of heat. The yield increased more in lower emissions scenarios (by 17% in RCP2.6) than in higher emissions scenarios. In the RCP8.5 scenario, the rising temperature adversely affected the growth process of winter wheat. The water footprint decreased by 10%, 11%, and 13% in the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively, indicating that climate change could improve water-use efficiency in the future.
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