RESEARCH

The Effects of Weather Data Sources on Simulated Winter Wheat Yield at Regional Scales

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Abstract

Urban heat island effects are created by large cities, and weather data collected in or near heat spots may be inappropriate for crop growth simulation. Research was conducted to evaluate the effects of different sets of historical weather data on DSSAT (Decision Support System for Agrotechnology Transfer) and APSIM (Agricultural Production Systems sIMulator) model simulations for winter wheat (*Triticum aestivum* L.) production in the North China Plain (NCP). Yield data from 10 recent years and three locations in the NCP were used for model calibration and validation. Three weather datasets including data from the exact experimental site, a nearby town and a nearby large city were used to obtain three sets of model parameters for each location. The different model parameters were further used to assess crop performance on regional scales. The well-calibrated and validated APSIM and DSSAT gave nearly identical average regional yields, but the model parameters in DSSAT were more sensitive to weather sources. Using the parameters derived from the source of city weather data tended to overestimate the yield in higher latitudes and underestimate the yield in lower latitude regions due to the higher thermal units and lower growth rates in the model parameters, which prolonged the growth duration. The results from this study also indicated that to reduce the bias in regional crop yield simulation, increasing the sites for model calibration should be recommended. During model simulation, the changes in model parameters to suit the source of the weather data increased the stability of the model performance but decreased the model sensitivity in responding to the changes in growing conditions.

Keywords APSIM · DSSAT · City weather data · Town weather data · Field weather data

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Introduction

Crop models are important tools for optimizing agronomic practices, improving resource use efficiency and mitigating climate change (Boote, 2019). Crop models were developed to study crop growth and development over one or more growing seasons, and they account for variation in weather throughout the seasons as well as variations in soil and management (Peng et al., 2020; Van Bussel et al., 2015). The crop models are designed to be applied with site-specific data such as daily weather data from nearby weather stations and generic local agronomic management (Van Bussel et al., 2016). With the increase in the use of crop models for regional agricultural system impact assessment, crop models are progressively being applied to large spatial scales, from regions within a country to globally. For a regional scale, the spatial changes in weather, soil and crop management should be considered during the modelling. In particular, meteorological data can exhibit considerable heterogeneity over

space and time due to the different surroundings (Kuwagata et al., 2018).

Often, the high uncertainty in crop modelling comes from the crop response to the temperature, which is used to calculate the thermal time (Wang et al., 2017). Asseng et al. (2015) reported that the model accuracy was impacted by the differences in model structures and parameter values that respond to temperature. Wang et al. (2017) reported that the uncertainty can be reduced by improving the temperature response functions in the models. However, crop models often contain parameters that cannot be measured directly but can only be inferred by a trial-and-error process in model calibration and validation known as model training. Model training is strongly influenced by the meteorological data used, and meteorological data obtained from different sources might affect the individual parameters used in the model.

Land-use changes such as irrigated agricultural conversion and plant transpiration can intensify or mask the microclimate by transforming the surface energy balance at the point or regional scale (Nocco et al., 2019). Urban microclimates are distinguished from cropland areas by differences in air temperature, humidity, wind speed and direction, and amount of precipitation (Peng et al., 2012). Compared with crop-growing land, urban zones have higher air temperatures called urban heat island (UHI). The temperature in the field can be affected by crop transpiration and soil evaporation, known as the "cooling effect (CE)", which does not occur in urbanized areas. Soil moisture significantly influences the surface climatic environments (Seneviratne et al., 2010), and can even act as a proxy (Nouri & Homaee, 2021). The impact of soil moisture on the surface environment changes with the different soil water supply conditions (Allen et al., 2021). The superposition of UHI and CE creates a significant difference between the agricultural land temperature and the nearby town/ urban land temperature.

In densely populated areas such as the North China Plain (NCP) there are towns and cities, with an average distance of 25 km between two towns and 100 km between two cities. The distance of the weather station from the big cities affects the daily weather data, especially the temperature, due to the UHI. The climatic conditions that prevail in a large metropolitan area differ from the climate of its rural surroundings (Peng et al., 2012). Weather data obtained from the national weather network in the NCP usually come from weather stations located in towns or cities. Weather data from the exact field are often missing. Therefore, the simulation of crop performance using crop models often depends on weather data collected not from the exact field sites. Due to the difference between city and farmland microclimates, the assessment of the impacts of climate change or management practices on agriculture may be biased. Therefore, the difference in metropolitan climate from the climatic conditions

obtained in the field should not be ignored for regional agricultural production simulations using models.

Currently, few studies have investigated the effects of models trained using data from different weather stations on regional yield assessments. To fill this knowledge gap, in this study, the Decision Support System for Agrotechnology Transfer (DSSAT) and Agricultural Production Systems sIMulator (APSIM), two popular crop growth simulation models that have been successfully applied in the NCP (Li et al., 2016; Sun et al., 2016; Wu et al., 2014; Zhang et al., 2013) and worldwide (Gaydon et al., 2017; Jones et al., 2003; Keating et al., 2003), have been used to test whether the different sources of weather data affect the simulated winter wheat (*Triticum aestivum* L.) production in the NCP to provide references for crop performance simulation in selecting weather data at regional scales. How the two well-known crop models responding to the differences in weather data were also evaluated in this study. The results might provide references for better understanding the effects of weather data sources on the performance of models and the reliability of those model parameters for evaluating future climate change on crop production.

Materials and Methods

Area of the Study

In this study, the regional crop simulation involved an area located between the eastern Taihang Mountains and the northern Yellow River (112.5° E–119.5° E, 34.8° N–40.5° N) in the North China Plain (NCP), covering the entire plain of Beijing, Tianjin, Hebei, and northwestern Shandong Province (Fig. 1). The total area is approximately 2.7×10^5 km^2, accounting for 16.3% of the land in total agricultural production in China. Total grain production reached more than 70 million Mg year^{-1}, accounting for 21% of China's production. Annual double cropping of winter wheat and summer maize is the dominant cropping system in the region (Kang & Eltahir, 2018). Three sites in this region were selected. The research sites were experimental stations of the China National Ecosystem Research Network (CNERN) located at Luancheng, Fengqiu and Yucheng (Fig. 1 and Supplementary Table 1).

Soil, Crop and Weather Data

The field experimental data on winter wheat were obtained from the three stations and were used to obtain model parameters. The data for winter wheat were obtained from the treatment with local irrigation and fertilizer application practices. Crop data, including varieties, major phenological stages, yields and management practices, were all recorded
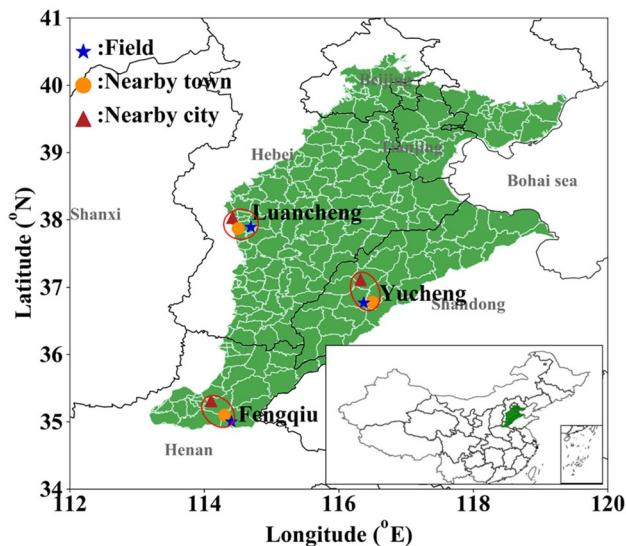
Fig. 1 Location of the study area, sites representing field, town and city environments in the North China Plain (NCP)

for the study duration at the three sites. Data for Fengqiu and Yucheng were obtained from the National Ecosystem Research Network of China (CNERN, http://cnern.cern.ac.cn), and data for Luancheng was obtained based on field studies. The growing conditions at the three stations can represent the surrounding farmland. Well-established long-term field studies and data were available for crop model calibration and validation. The three field experimental stations all have weather stations located inside the crop growing field, which can represent the weather data obtained from the field, to distinguish the weather data obtained in a town or a city for crop model simulation.

Detailed field experimental data, including soils, tillage, fertilization, phenology, aboveground biomass at anthesis and maturity, yield and management practices for eight growing seasons at Luancheng station from 2007 to 2015, for ten growing seasons at Yucheng and Fengqiu stations from 2005 to 2014, were used for model calibration and validation. The winter wheat cultivars used were all *Jimai22* for the three stations.

Observed daily weather data for solar radiation, minimum and maximum temperatures, precipitation, wind speed and air humidity during the period of 2008–2015 at Luancheng station and during the period of 2005–2014 at Fengqiu and Yucheng stations were used as weather data obtained under field conditions.

To examine the possible effects of weather data sources on the model parameters, weather data from nearby counties and large cities were used. Towns and large cities nearest to the three field experimental stations were selected. The detailed geographic locations of the towns and cities are shown in Supplementary Table 1 and Fig. 1. The daily

weather data from the three towns and cities were obtained from the China Meteorological Bureau, which was used for model validation and calibration to obtain model parameters. Soil hydraulic parameters at the three stations (Supplementary Table 2) were obtained from previous studies, i.e., Luancheng soil parameters from Sun et al. (2016), Yucheng from Wang et al. (2007), and Fengqiu from Chen (2008).

Crop Models and Parameterization

In this study, two popular models, APSIM and DSSAT, were applied. For both models, the key crop model parameters that are closely related to crop growth, development and grain formation were identified by modelling. Based on the detailed field trial data on wheat response (phenology and yield) to agronomic management practices and environmental conditions at the three sites, key parameters were selected for the two models (Ma et al., 2020; Zhao et al., 2014). The traditional trial-and-error method was used for APSIM and DSSAT calibration.

Initially, the calibration of both models was based on the previous parameters in this region (Sun et al., 2015; Zhang et al., 2013) and was further adjusted based on the experimental results at the three sites. The parameter calibration process was as the following: Step 1, input parameters from previous research; Step 2, the cultivar parameters were trimmed using a trial and error method to match the simulated crop anthesis and maturity dates to the observed data from 2004 to 2009 at Fengqiu and Yucheng and from 2008 to 2012 at Luancheng. Step 3: The model was run with the trimmed crop parameters, and the performance was evaluated according to the biomass and grain yield. After calibration, the model was further validated using the experimental data from 2010 to 2014 at Fengqiu and Yucheng and from 2013 to 2015 at Luancheng. For all the simulations, irrigation and fertilizer were applied according to the actual practices.

During the calibration and validation of the models, three sets of weather data obtained from the field, town and city were used separately to obtain the parameters for the two models, therefore, there were three sets of model parameters for each location. Totally, nine sets of crop model parameters were produced to simulate the regional yield of winter wheat in the NCP for each of the two crop models used in this study. At each site and for each set of crop parameters, the differences between simulated and observed flowering and maturity dates were less than 3 days, and the discrepancies between observed and simulated yields were less than 20%.

Model performance was evaluated using the slope and the coefficient of determination (R^2) of the regression lines between simulated and observed values. The Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE) and Nash–Sutcliffe Efficiency (NSE) are

used to quantify the deviation of the simulated results from the observed data as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (S_i - O_i)^2} \qquad (1)$$

$$NRMSE = \frac{RMSE}{\overline{O}} \qquad (2)$$

$$NSE = 1 - \frac{\sum (O_i - S_I)^2}{\sum (O_i - \overline{O})^2} \qquad (3)$$

where S_i is the simulation value, O_i is the observation value, $\overline{O}$ is the mean of observation values, and n is the number of simulation or observation values.

Model Performance Using Different Sets of Parameters on a Regional Scale

Nine sets of model parameters drove the model simulation on the regional scale using APSIM and DSSAT. The regional yield of winter wheat was simulated from 2008 to 2016. Regional weather data from 2008 to 2016 were obtained from the China Meteorological Assimilation Driving Datasets (CMADS). Data sources for the CMADS series include nearly 40,000 regional automatic stations under China's 2421 national automatic and business assessment centers (Meng et al., 2019). The spatial

resolution for CMADS V1.1 was 1/4°. At least one weather station was included in each county in the NCP. The regional soil physical properties of NCP were extracted from a raster dataset produced by Dai et al. (2013), including soil bulk density (BD), saturated volumetric water content (SAT), drained upper limit (DUL), 15-bar lower limit (LL15), and soil N and organic matter content for different soil layers. Figure 2 presents the modelling processes for the regional scale yield evaluation in this study. During the simulation, automatic irrigation and fertilization were turned on to ensure that enough water and nutrients were applied to the crop. Other management practices, such as sowing date and sowing rate, followed the local practices.

The weather stations located inside the field represent the real growing environments of the crops. Therefore, the yield simulated with the parameters derived from field weather data was taken as the benchmark in this study. To assess the model parameters derived from other sources of weather data on model performance at a regional scale, yield differences simulated using different model parameters were compared. $D_{field-town}$ (yield simulated using field weather data derived parameters minus that from town), $D_{field-city}$ (yield simulated using field weather data derived parameters minus that from city), and $D_{town-city}$ (yield simulated using town weather data derived parameters minus that from city) were calculated for the comparison. Phenological differences in maturity simulated using different model parameters were also compared in the same way as the yield. $DAS_{field-town}$, $DAS_{field-city}$ and $DAS_{town-city}$ represent the difference in maturity days using different model parameters defined the same as the yield difference.

Fig. 2 The processes of model parameter derivation and regional yield simulation considering the source of weather data
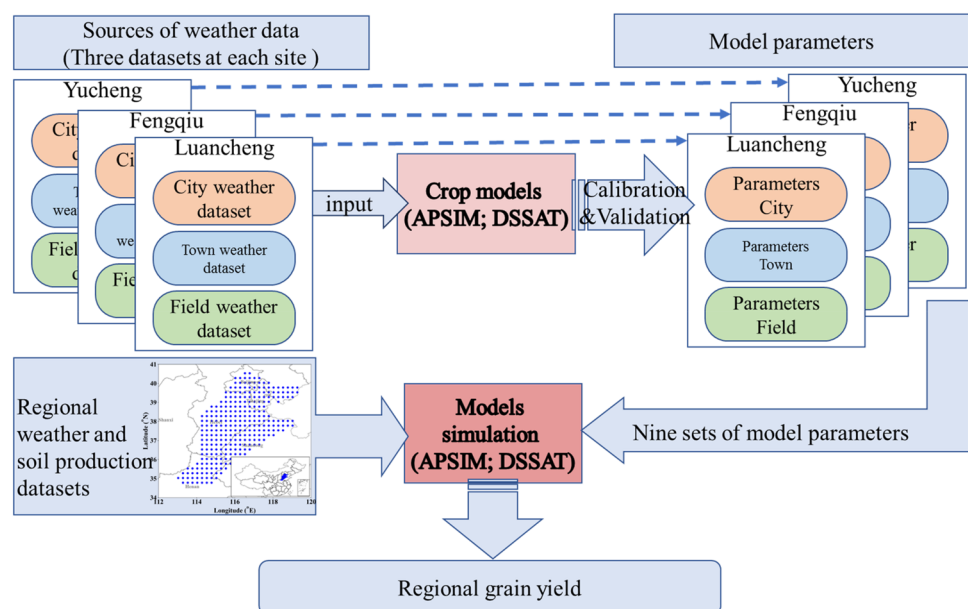
Data Analysis

The open-source programming language Python data analysis packages were used in this study, including "Pandas" (https://pandas.pydata.org/) for data processing and simple statistical analysis, "Scipy" (https://www.scipy.org/) for linear regression and parameter estimation, "Seaborn" (https://seaborn.pydata.org/) and "Geopandas" (https://geopandas.org/) for charting.

Results

Mean Daily Weather Data at Different Locations During Winter Wheat Growing Seasons

There was a trend of a significant ($p < 0.05$) increase in daily minimum temperature (T_{min}) over time at all locations but with a much greater increase for the cities than that for the fields (Fig. 3). There was also a significant ($p < 0.05$) increase in daily maximum temperature (T_{max}) over time, but with the similar increase trends for fields, towns and cities. Seasonal radiation showed a declining trend, and the change in seasonal rainfall was smaller. Generally, cities had higher temperatures and reduced radiation than small towns and fields. Under the climate
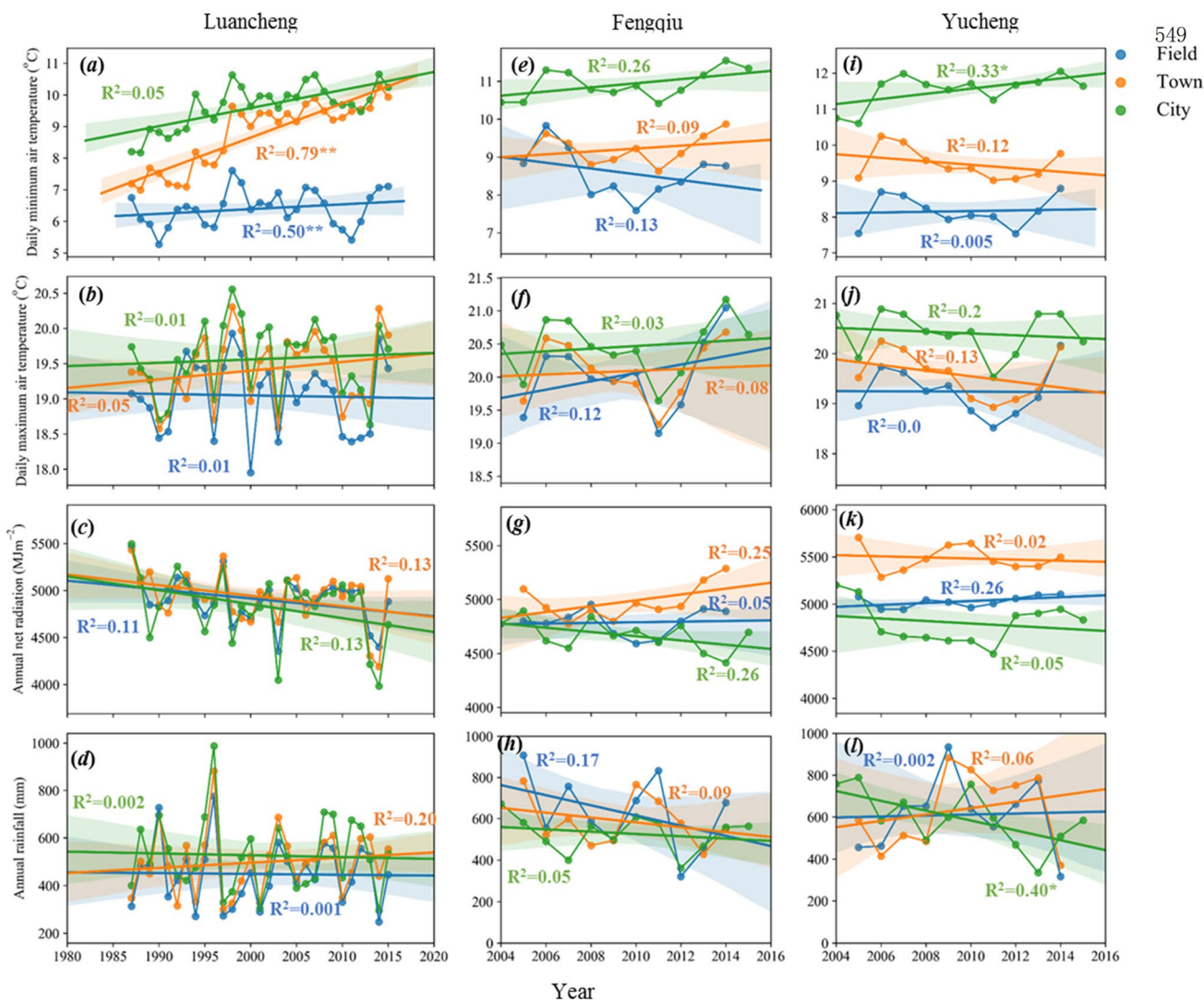
Fig. 3 Comparing the average seasonal weather data obtained at three locations (field, nearby town and city) for Luancheng site (**a–d**) from 1987 to 2015, Fengqiu site (**e–h**) from 2005 to 2014, and Yucheng site (**i–l**) from 2005 to 2014 during winter wheat growing seasons

change background, the increase in temperature, especially T_{min}, was much greater in large cities than that in other locations. The difference in weather factors under different environments was becoming greater. The average seasonal weather factors were obtained from different locations for the last 10 seasons (Supplementary Table 3). The results indicated that weather factors were affected by the locations of the weather station from the large cities, with T_{min} being the most affected factor. T_{min} values under the field conditions were on average 18% and 12% lower than the T_{min} values in cities and towns, respectively, for the three sites. There were also variations in radiation and precipitation among the different locations.

Model Parameters Derived from Different Weather Sources

Tables 1 and 2 list the major parameters derived using different sources of weather data. All the parameters fall in the scope of the rational values of the two models. For APSIM (Table 1), the parameters related to thermal time differed the most using the three sources of weather data. The parameter value of thermal time was the highest using the city weather data at all locations, next was from the town weather data source, and the lowest was from the weather data under the field environment. In contrast, the parameter value of the potential grain filling rate was the highest using the weather data at two locations, followed by the town weather data, and the lowest was from the

Table 1 The derived crop parameters for the APSIM using different sources of weather data to simulate the yield of winter wheat

Source of weather data	Luancheng			Fengqiu			Yucheng		
	Field	Town	City	Field	Town	City	Field	Town	City
photop_sens	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.2	2.94
vern_sens	2.4	2.4	2.4	2.4	2.4	2.4	2.4	2.4	3.58
tt_end_of_juvenile	400	515	525	531.7	531.7	601	418	481	408
tt_floral_initiation	555	610	615	600	650	710	596	627	698
startgf_to_mat	550	600	600	600	670	700	580	580	630
potential_grain_filling_rate	0.0025	0.0019	0.0018	0.00233	0.00233	0.00233	0.0040	0.0028	0.0018
potential_grain_growth_rate	0.001	0.001	0.001	0.0008	0.0008	0.0008	0.0005	0.0005	0.001

photop_sens: Sensitivities to photoperiod

vern_sens: Sensitivities to verbalization

tt_end_of_juvenile: The thermal time of potential period from end of juvenile stage to terminal spikelet

tt_floral_initiation: The thermal time of potential period from terminal spikelet to start flowering

startgf_to_mat: The thermal time of potential period from start flowering to end of grain filling

potential_grain_filling_rate: The potential rate of grain filling

potential_grain_growth_rate: Grain growth from flowering to grain filling

Table 2 The derived crop parameters for the DSSAT using different sources of weather data to simulate the yield of winter wheat

Source of weather data	Luancheng			Fengqiu			Yucheng		
	Field	Town	City	Field	Town	City	Field	Town	City
P1V	41	60	49	48	52	63	47	35	54
P1D	14	71	10	34	2	70	36	92	25
P5	565	463	609	529	694	346	608	721	434
G1	23	24	21	15	24	23	20	22	20
G2	47	33	49	59	44	36	50	33	50
G3	1.5	1.9	1	1	1	1.2	1	1.4	1
PHINT	88.9	95	96.8	90.1	95.5	101.5	92.8	95.2	99.3

P1V (Days, optimum vernalizing temperature, required for vernalization)

P1D (Photoperiod response (% reduction in rate/10 h drop in pp))

P5 (Kernel number per unit canopy weight at anthesis (#/g))

G1 (Standard kernel size under optimum conditions (mg))

G3 (Standard, non-stressed mature tiller weight (including grain) (g dwt))

PHINT (Interval between successive leaf tip appearances (°C.d))

weather data under the city environment. However, for the Fengqiu site, the potential grain filling rate was the same for the three sources of weather data. Generally, the temperature difference among the locations affected the derived crop parameters for APSIM, and using weather data from high-temperature environments tended to produce higher thermal units and lower growth rates for the model parameters.

For DSSAT (Table 2), a difference existed for all the major model parameters derived from the three sources of weather data, but no certain pattern in parameter changes for P1V (days required for vernalisation), P1D (photoperiod response), P5 (kernel number per unit canopy weight at anthesis), G1 (standard kernel size) and G3 (standard tiller weight) was observed, except for PHINT (interval between successive leaf tip appearance). Similar to APSIM, the thermal unit requirement was increased for crop growth using weather data from city environments.

Grain Yield of Observation vs Simulation

Figure 4 shows that both the APSIM and DSSAT models can simulate winter wheat yields obtained from the three locations using different sets of weather data (field, town, and city environments). Both models could capture the seasonal variation in yield. The observed average yield was 7396 kg ha^{-1} at Luancheng, 7763 kg ha^{-1} at Fengqiu, and 7471 kg ha^{-1} at Yucheng. The simulated average yields were 7371 kg ha^{-1}, 7665 kg ha^{-1} and 7448 kg ha^{-1} for the three sites. The RMSEs between the observed and simulated yields for APSIM were 488 kg ha^{-1}, 615 kg ha^{-1} and 472 kg ha^{-1} using city, field and town weather datasets, respectively. The RMSEs between the observed and simulated yields were 424 kg ha^{-1}, 438 kg ha^{-1}, 426 kg ha^{-1}, respectively, for DSSAT. The mean NRMSE values for APSIM and DSSAT were 6.97 and 5.68, and the NSE values were 0.48 and 0.64, respectively (Supplementary Table 4). The results indicated that by adjusting the crop parameters, weather data from different sources could be used for simulating crop production.

Fig. 4 Observed yield versus simulated grain yield for winter wheat for ten seasons with three trained parameters derived from using different sources of weather data (obtained from field, town and city environments) at three locations (Luancheng, Fengqiu, Yucheng) in the North China Plain
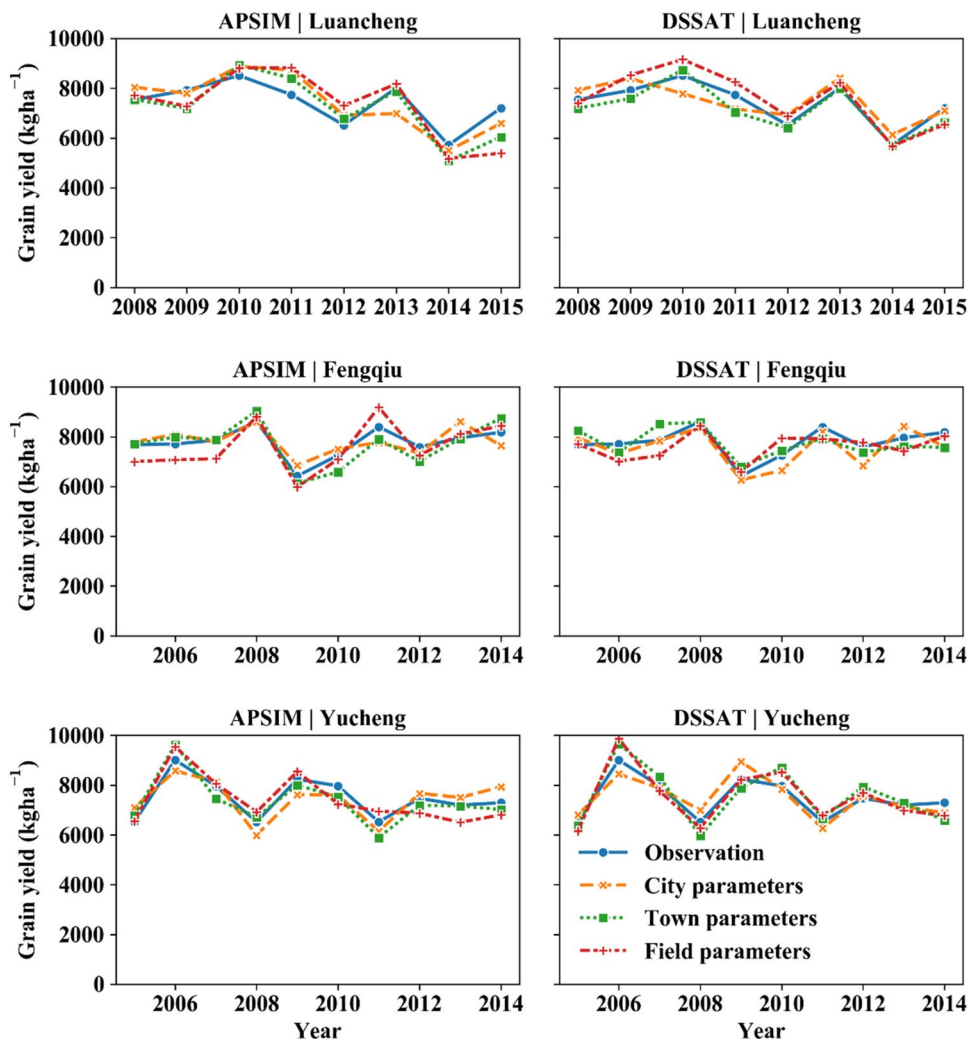
Spatial Variation in Yield Differences Using Different Sets of Model Parameters

The regional distribution of simulated winter wheat yields averaged for the seasons of 2008–2016 is shown in Figs. 5 and 6. The simulation was conducted separately using the nine sets of parameters derived with different sets of weather data for APSIM (Fig. 5) and DSSAT (Supplementary Fig. 1). The results indicated that the simulated average regional yield was quite similar using the parameters from different sources of weather data for a certain location. For example, with the APSIM model, the average regional yields were 9118, 9135 and 9104 kg ha^{-1} using the three sets of parameters derived from the Luancheng site. The values were 9544, 9475 and 9569 kg ha^{-1} at the Fengqiu site and 9391,

9305 and 9335 kg ha^{-1} at the Yucheng site, respectively. The results also indicated that the parameters from the three locations produced slightly different average regional yields, with the yield from the Fenqiu site being 4.5% higher than the yield from Luancheng and 2% higher than the yield from Yucheng. The same results were obtained with the DSSAT model. The location of the Fengqiu site is at lower latitudes, and the thermal conditions at this site were higher than the thermal conditions at the other two sites. The results might indicate that the model parameters derived from locations with higher thermal conditions tended to produce a higher yield than the model parameters derived from locations with lower thermal conditions.

Although the regional average yield using the three sets of parameters derived from different sources of weather data
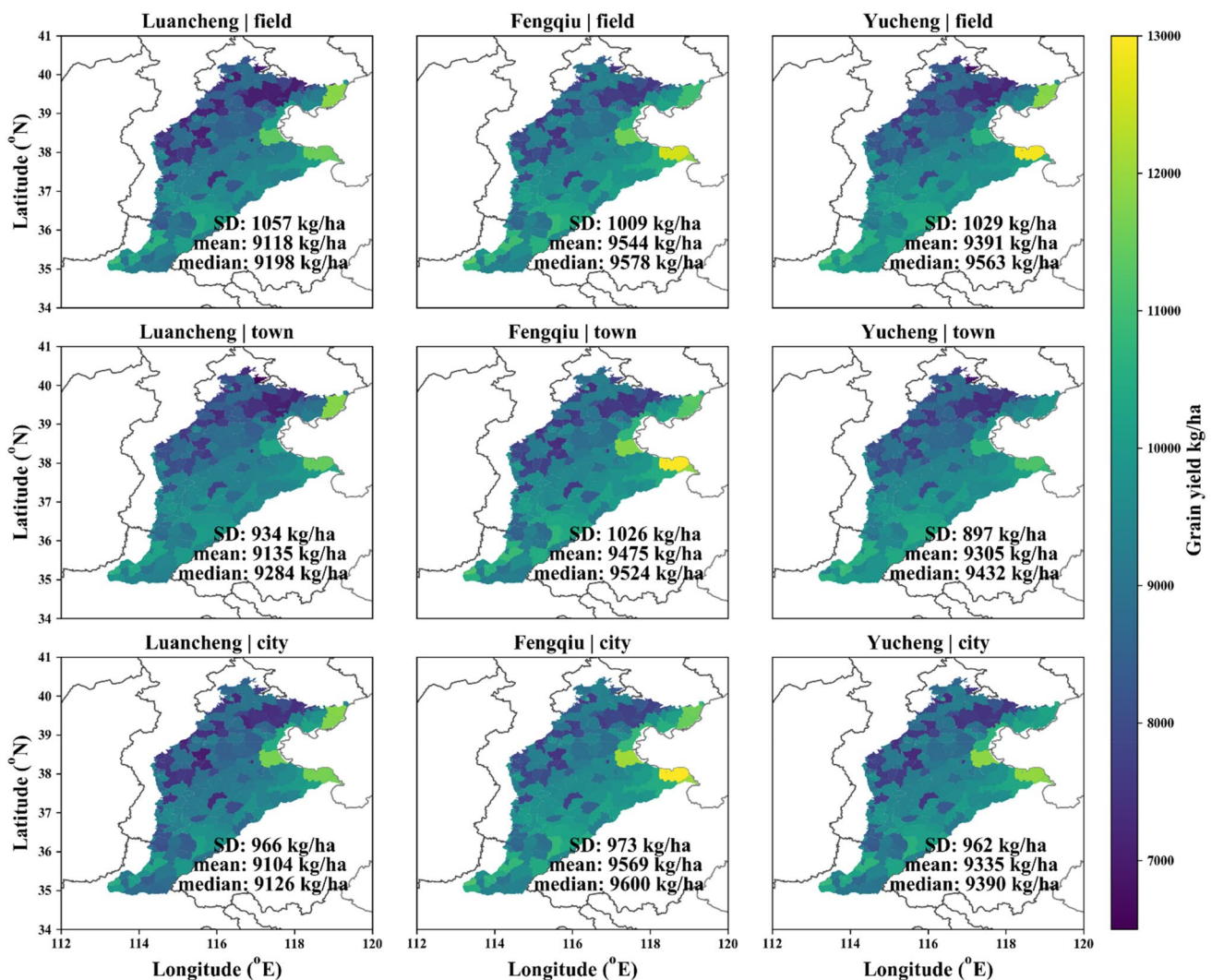
Fig. 5 The average regional winter wheat yield during 2008–2016 simulated using different sets of model parameters derived from different locations and different sources of weather data in the North China Plain using APSIM model (Field: model parameters derived from weather station located in field; Town: model parameters derived from weather stations located at a nearby town; City: model parameters derived from weather stations located at a nearby city)
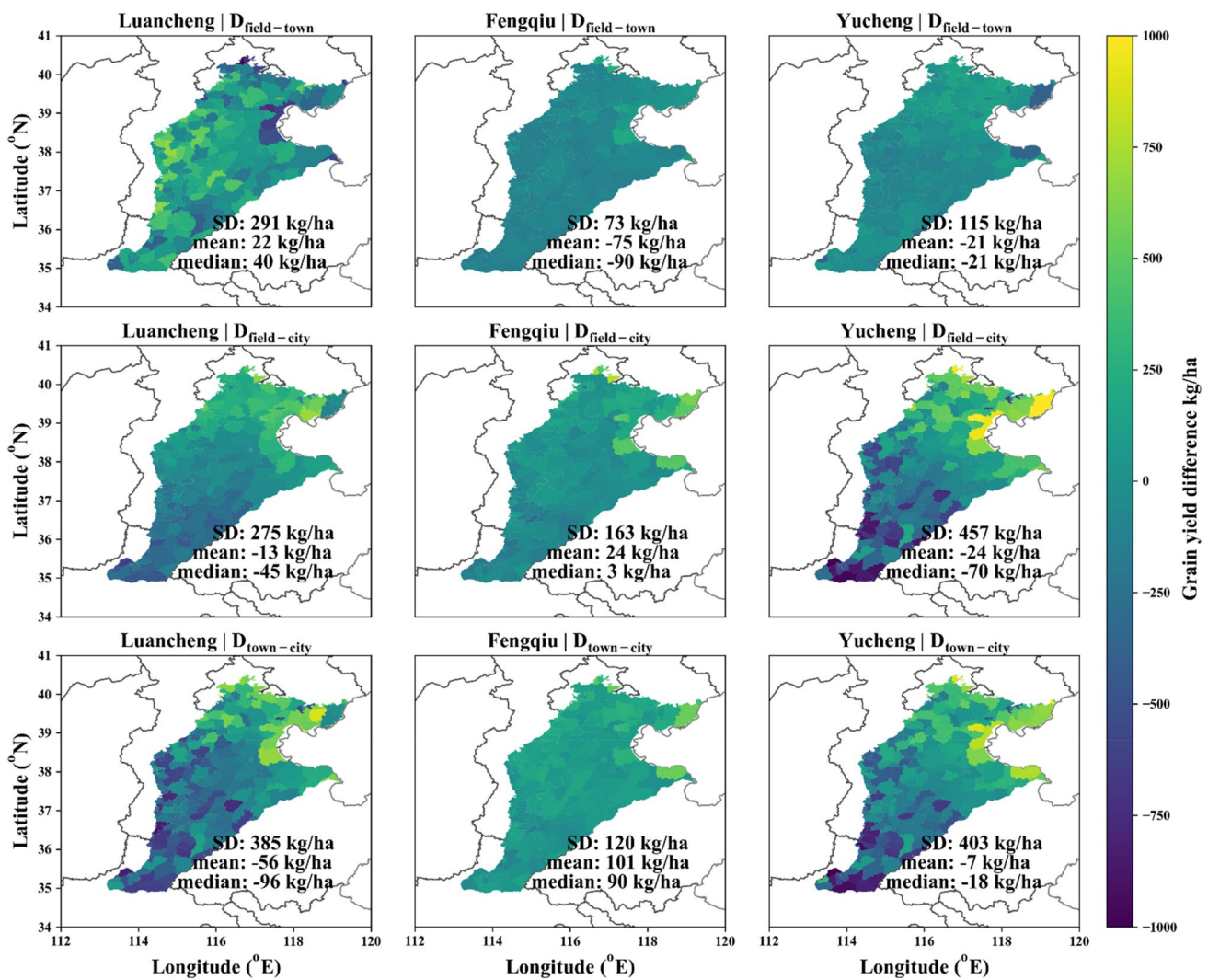
Fig. 6 The average yield differences at regional scale between winter wheat yield simulated with different model parameters derived from the weather data under field, town and city environments at three locations using APSIM. ($D_{field-town}$, $D_{field-city}$, $D_{town-city}$ stand for the simulated yield difference using model parameters derived from field and town, from field and city, from town and city, respectively)

was quite similar, regional yield variations were observed. The yields simulated using field or town weather-derived parameters were similar, indicating that the difference of the weather conditions between a town and the field was rather smaller. The larger $D_{field-city}$ and $D_{town-city}$ values indicated that the model parameters derived from city weather stations affected the model simulation. The trends in yield differences for APSIM and DSSAT were similar.

The regional $D_{field\ town}$, $D_{field\ city}$ and $D_{town\ city}$ are shown in Fig. 6 (for APSIM) and Supplementary Fig. 2 (for DSSAT). Except for $D_{field-town}$, the other two differences simulated with the DSSAT and APSIM models were all significantly correlated with latitude (Fig. 7) ($p < 0.01$). The yield simulated with the parameters derived from the field or town weather source tended to produce a higher yield in regions with lower latitudes and lower yield in

regions with higher latitudes as compared with the yield simulated with the parameters derived from the city weather source. Model parameters derived from the three sources of weather stations indicated that more thermal units were required using the city weather data, followed by the town and the field. Accompanying the higher thermal unit values, a lower growth rate in the model parameters was observed using city weather data (Tables 1, 2). The difference among the model parameters in thermal units and growth rates produced different phenologies (Supplementary Figs. 3–6). Figure 8 indicates that using the parameters derived from the city environments produced longer maturity days, and the difference in simulated maturity days increased with the increase in latitude with the other two environments. The larger increase
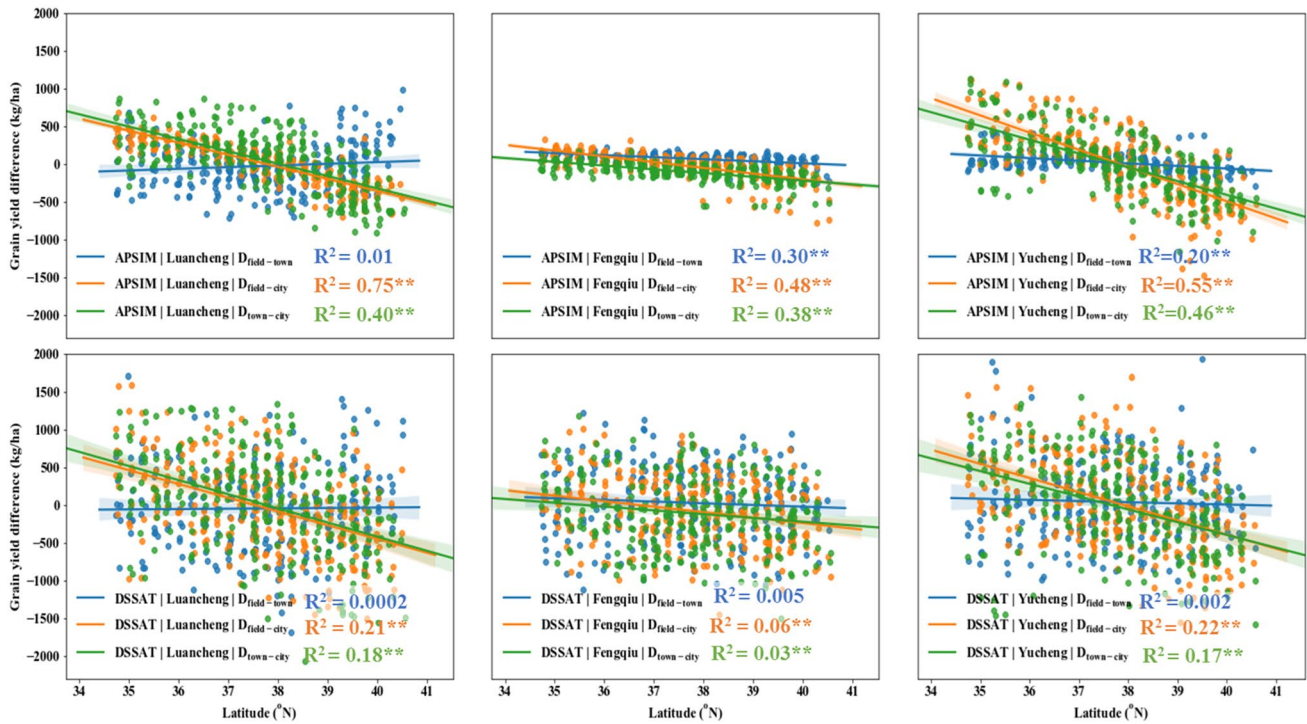
Fig. 7 The correlation analysis of the three yield difference with the latitude for $D_{field-town}$, $D_{field-city}$, $D_{town-city}$ using APSIM and DSSAT. ($D_{field-town}$, $D_{field-city}$, $D_{town-city}$ stand for the simulated yield difference using model parameters derived from field and town, from field and city, from town and city, respectively)
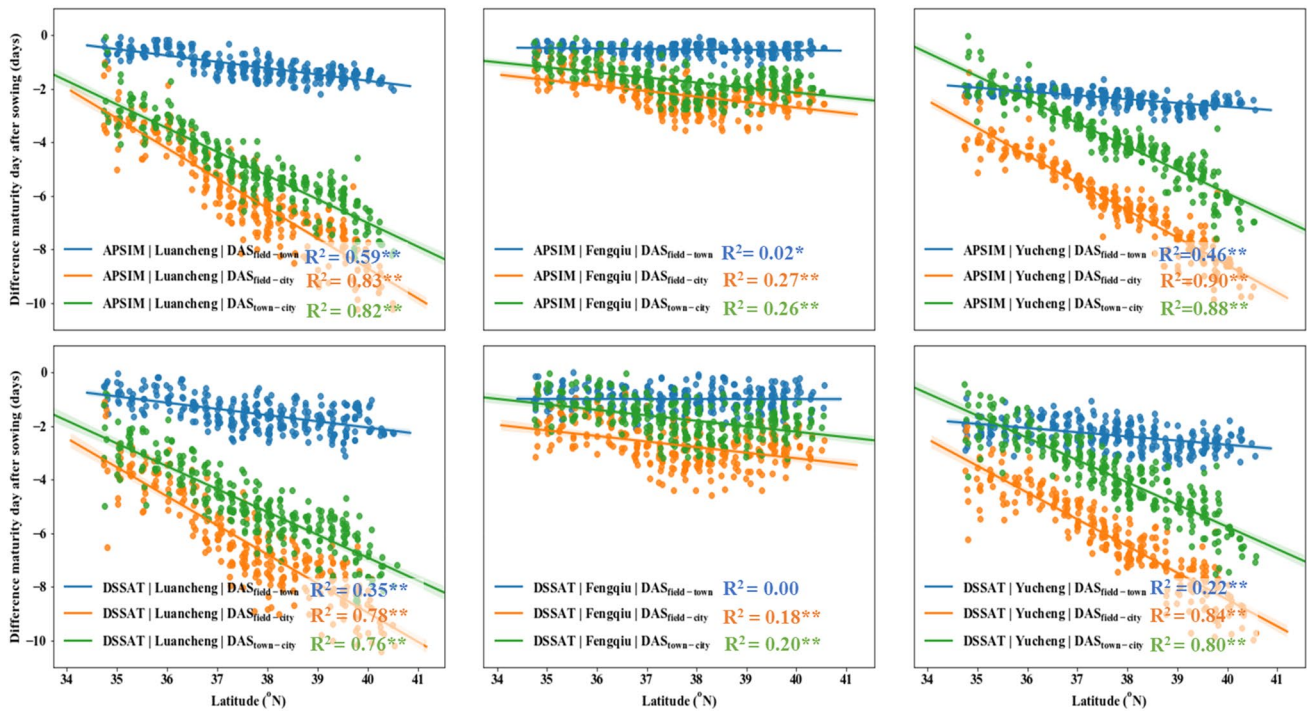
Fig. 8 The correlation analysis of the three phenology difference in maturity day with the latitude for $DAS_{field-town}$, $DAS_{field-city}$, $DAS_{town-city}$ using APSIM and DSSAT. ($DAS_{field-town}$, $DAS_{field-city}$, $DAS_{town-city}$ stand for the simulated phenology difference using model parameters derived from field and town, from field and city, from town and city, respectively)

in growing duration using the city parameters resulted in higher simulated grain production in higher latitude regions.

Comparing the Performance of DSSAT and APSIM

Figure 9 shows the average simulated regional yield using APSIM and DSSAT. The regional average simulated yield was 9119 kg ha^{-1} using the APSIM model based on the crop parameters derived from Luancheng, 9530 kg ha^{-1} from Fengqiu, and 9344 kg ha^{-1} from Yucheng. The three values were 9121, 9535 and 9314 kg ha^{-1} using the DSSAT model, respectively. The results indicated that the two models performed nearly identically in regional yield simulations. Some differences existed between the two models in the response to the model parameters derived from different sources of weather data, with DSSAT being more sensitive to the model parameters, as shown in Fig. 7.

The yield difference among the three sets of parameters was greater with DSSAT than with APSIM. Possible reasons might be related to the model parameters used in the two models, with all seven model parameters changing with the

Fig. 9 Comparing the yield simulated using DSSAT and APSIM using the model parameters derived from the three locations

sources of weather data for DSSAT (Table 2), but only part of the parameters changed for APSIM (Table 1). Figure 7 also shows that the yield differences using the three sets of model parameters derived from the three sources of weather data at the Fengqiu site were much smaller than the yield differences at the Luancheng and Yucheng sites for APSIM. The reason might be related to the difference in the three sets of model parameters being only related to the thermal units, and the growth rate parameters did not change at the Fengqiu site. Therefore, fewer changes in model parameters to suit the source of the weather data increased the stability of the model performance but decreased the model sensitivity in responding to the changes in growing conditions. Comparing the performance of the two models, if there was more accurate climate data in a region, DSSAT should be used, and if the availability of climate data was less, APSIM might be better.

Discussion

Differences in Source of Weather Data and Their Impacts on Yield Simulations

In this study, models trained in a warmer urban microclimate versus a cooler town or field microclimate environment could simulate the seasonal crop yield, and the observed yields were reproduced well. No apparent difference was found in the simulated yields of these models trained using different sources of weather data. Theoretically, the yields should be different for different climates (Rötter et al., 2012). Due to the different training datasets were used to derive model parameters to fit the respective environments, and the observed yield could be simulated using different sets of model parameters (Supplementary Table 3, Table 1). The thermal units for the model parameters derived using the urban environmental weather data were higher than the thermal units for the model parameters derived using either the field or town environmental weather data, which might result in underestimating the negative effects of temperature rise on crop production. The growth rate parameter was reduced using weather data from warmer environments, which would increase the duration of the growing season, and the extended growing duration generally resulted in higher production. Changes in the parameters for crop models might produce opposite results. Therefore, the weather datasets that drive model calibration and validation should be carefully selected for the corresponding application ranges to extend them regionally; otherwise, they may introduce biases in the simulations.

In the regions of this study, city temperature was significantly higher than the temperature under town and field microclimate environments, as was the case at all three
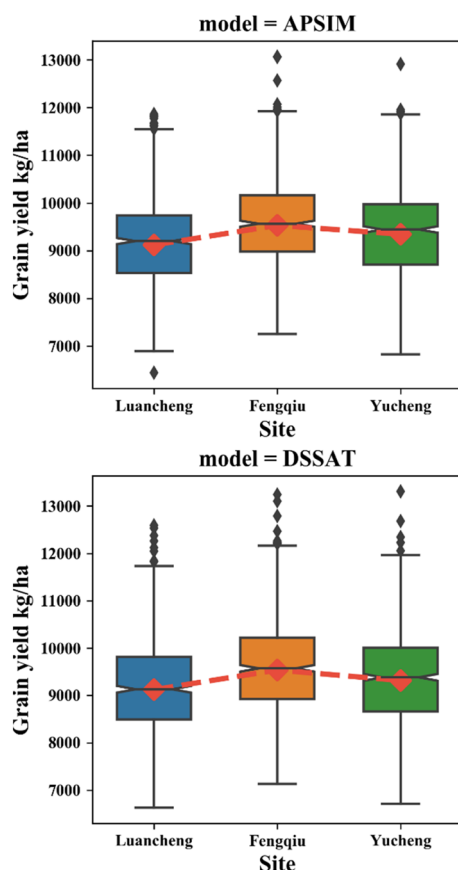
locations (Supplementary Table 3). As urbanisation is still proceeding at a rapid pace, the heat island effect will be strengthened and will further widen the microclimate difference between cities and fields (Stone, 2007). Therefore, for crop model calibration and validation, the source of weather data should be considered in densely populated regions.

Models Trained at a Single Point for Regional Simulation

Due to the lack of observation data, models validated based on field-scale simulations upscaled to regional levels have been a fundamental issue in model research. The results from this study indicated the variation in the winter wheat yield simulated using the model parameters derived at the three locations, with the highest yield obtained from the model parameters derived in warmer conditions. Using models trained at specific locations, upscaling to a large region or even to the whole globe is a challenging issue (Liu et al., 2013). Van Bussel et al. (2016) reported the use of spatial samples for regional simulations or dividing climate zones and then performing zonal simulations. Both of these methods can improve the accuracy of simulations on the regional scale to a limited extent.

To better simulate crop performance on a regional scale, the resolution of weather data is another factor to be considered. The observation of regional meteorological data is a costly project, and there is often a lack of meteorological data in many areas, especially with only a few stations located inside the field environment where crops are growing. Kuwagata et al. (2018) and Peng et al. (2012) reported the climatic conditions that prevail in a large metropolitan area and that differ from the climate of its rural surroundings. The results from this study indicated that there were differences in the spatial distribution of the simulated yield from the trained models based on different sources of weather data. In particular, the results from this study indicated that the model trained from the city environment tended to overestimate the crop yield under cooler conditions. Using such trained models, therefore, the negative effects of climate change might be underestimated in high latitude areas. The results also indicated that the yield difference simulated using different sets of parameters was correlated with the latitude degree. Therefore, covering as much latitude as possible in a region in training models to offset simulation bias due to environmental variations would be desirable.

Model Parameter Uncertainties

Due to the complexity of the biophysical mechanisms of crop development, growth, and grain formation in interactions with genotype, management and environment, the current models may not be able to identify all these processes. Consequently, it is essential to calibrate and validate crop models by adjusting model parameters to better fit the observation data (He et al., 2010). The uncertainties of crop models are related to those model parameters, and the uncertainties in parameters of crop models can result in a large bias in simulating grain yield (Tao et al., 2009, 2018). The modelling error was expected to reach zero as the true model parameters were obtained. Wallach (2011) reported that crop models do not have this property, crop models are misspecified, and under this misspecification, model calibration tends to minimize prediction errors for the variables and sampled populations used for calibration. For simulations on regional scales, the model parameters obtained were often limited to several sites without fully covering all the environment in a region, which might weaken the reliability of the simulated results. More detailed input data is generally recognized to improve the simulation of spatial distributions (Manevski et al., 2019). Therefore, using observed data at multiple sites for model calibration and validation is quite important to reduce the uncertainties in model parameters.

It should be noticed that the results of this study were obtained without water and nitrogen stresses. Under water stress conditions, the cooling effect of irrigation is weakened due to the reduced crop transpiration and soil evaporation, and water stress generally would shorten the growth period of crops and reduce crop yield. The simulated results of this study indicated that the simulated crop yields were higher in cities with higher temperatures. The main possibility might be that the increase in temperature would reduce the freezing damage of winter wheat during the overwintering period, lead to an earlier recovering and flowering period, prolong the grain-filling stage and ultimately increase the grain yield. Therefore, opposite results could occur under other water and nitrogen conditions.

Assessing Crop Performance Under Climate Change

In assessing the effects of climate change on crop performance, crop models are often used, and the model parameters are often derived from the current growing conditions. The results from this study indicated that the location of the weather station providing the weather data for model calibration and validation affected the derived model parameters. Temperature is the main influencing factor in plant growth, which controls the development of crops in the form of thermal time and strongly influences crop yield (Xiao et al., 2017). Lobell et al. (2007) reported that declining yields due to rising temperatures will threaten food security with the growing population under global climate change. In North China, higher temperature increases winter wheat yield in the absence of moisture stress, while yield decreases in the presence of a moisture deficit (Yan et al., 2020). The

model parameters tended to have higher thermal units and lower growth rates using weather sources with warmer temperatures for model calibration. Therefore, the difference in the model parameters would influence the estimation of climate change on crop performance. This issue should be considered in climate change studies.

Conclusions

This study showed that the urban heat islands (UHIs) of cities caused the differences in weather factors among nearby weather stations. Crop model validation using different sources of weather data produced different model parameters. These differences in model parameters influenced the simulated yield on regional scales. The model parameters derived with weather data in a warmer environment tended to have higher thermal units and lower growth rates, and using those model parameters tended to produce longer crop growth durations and resulted in the overestimation of crop production in cooler regions. Thermal units and crop growth rate are important model parameters in assessing crop performance under climate change; therefore, the weather source for model calibration and validation should be considered in densely populated regions. The results from this study also indicated that crop models with more parameters responding to weather data input would produce larger yield variations in regional yield simulations. The stability and sensitivity of the model performance were related to the model parameters and could be considered in selecting crop models. To further improve simulation accuracy at regional scale, weather data in the field environment whenever possible for the model calibration and simulation should be recommended.

Data availability The datasets generated or analysed during the current study are available from the corresponding author on reasonable request.

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