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Research paper

Spatio-temporal distribution of sugarcane potential yields and yield gaps in Southern China

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ABSTRACT

The sustainability and production capacity of sugarcane (*Saccharum officinarum (L.)*) in Southern China is essential to ensure sugar security in China, yet potential crop yield and yield gap (the difference between actual and potential crop yield) of sugarcane is poorly known. In this study, the sugarcane growth and development model, QCANE, was validated for sugarcane phenology, stalk height, and yields, then used to simulate potential yields and yield gaps of sugarcane in Southern Chine (SC) between 1970 and 2014. Simulated potential yields decreased as longitude and latitude increased, driven by spatial variation in solar radiation and maximum temperature. The gap between potential and water-limited yields was noticeably larger in Yunnan province because of the prevalence of seasonal water deficiency. However, nitrogen stress was the dominant driver of the yield gap, given the abundant precipitation in SC. Across SC, large variation in the yield gap between water-and-nitrogen limited yields and on-farm yields was observed for different counties, a difference that was usually larger than the local yield gap. Averaged across SC, on-farm sugarcane yields were only 27% of potential yields, 31% of water-limited yields, and 52% of nitrogen-limited yields. This result highlights considerable potential to significantly increase sugarcane production by improving varieties, government support, effective management measures such as fertilization, irrigation, and mechanization.

1. Introduction

Sugar is a major component of global agricultural trade. China is the world's third largest sugar producer, after Brazil and India, and the sugar industry contributes approximately 0.1% of its total GDP (Li and Yang, 2015). However, sugar production in China cannot currently meet the domestic demand driven by rapid growth in sugar consumption (Li and Yang, 2015). Stimulated by the large gap in sugar price between domestic and international markets, sugar importation has been steadily increasing in China. In the crushing season, the cost of sugar production in China was around 4000 RMB/tonne, double the cost of sugar from the mechanized producers in Brazil and Australia (Yinggang et al., 2013). At the same time, the international sugar market remains distorted, because the international sugar market price has traditionally been lower than average world production costs (Zhixiong, 2012). Consequently, sugar security is of major concern to the sugar industry and governments in China. One way to address this is by identifying pathways for improvement in sugar production in China to raise yields and lower costs (Li and Yang, 2015).

Southern China (SC), including Guangdong, Guangxi, Hainan, and Yunnan provinces, is the major sugarcane (*Saccharum officinarum (L.)*) producing region of China, where sugarcane plantings cover around 1.7 million hectares. During the 2012–2013 crop season, sugarcane production in SC accounted for more than 95% of the nation's sugarcane production (122.4 million tonnes) (National Bureau of Statistics of China (NBSC), 2014). However, average yields remain far below levels

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achieved by countries such as Brazil and Australia, while inter-annual variation in yield is greatly affected by variability in precipitation rates (Li, 2004).

The challenge is to utilize existing farmland to increase sugarcane yields as there is limited scope for expansion of land available for sugarcane production. Yield gap analysis is a powerful quantitative framework that can assist with addressing this challenge (Stuart et al., 2016; Van Ittersum et al., 2013). Several studies have already utilized this approach for wheat, maize, and rice in some regions in China (Li et al., 2014; Liu et al., 2016a,b; Lu and Fan, 2013; Meng et al., 2013). Globally, the yield gap atlas project has been to estimate the yield gaps for major food crops across all crop-producing countries (www.yieldgap.orgwww.yieldgap.org). This research has emphasized the strong link between the size of the yield gap and additional production capacity on exiting planting area for a given crop and region. However, there are few comprehensive documentations of sugarcane potential yields and yield gaps in SC. Moreover, there are no regional analyses of the constraints due specifically to water, nitrogen, and other factors for sugarcane yield in SC in recent years. This knowledge gap makes it difficult for sugarcane producers and decision makers to improve sugarcane productivity under current and future climate conditions.

Yield gap is the difference between different yield levels, such as potential yield, attainable yield, and actual yield, and the gap between different yield levels represents a different yield potential (Lobell et al., 2009; Lobell and Ortiz-Monasterio, 2006; Rabbinge, 1993; Zhijuan, 2013). Potential yield is the yield that would be achieved without water and nutrient limitation and without the influences of weeds, pests, and diseases (Evans and Fisher, 1999; Fischer, 2015). Potential yield is also limited by climate factors like solar radiation and temperature (Casanova et al., 1999; Liu et al., 2012). Attainable yield is the yield achieved when water and/or nutrients are limited during part of, or all of, the growing season. Attainable yield is reduced to actual yield through inappropriate management of weeds, pests, and diseases (Lobell et al., 2009; Mueller et al., 2012). Crop modelling is widely used to analyze crop yield gaps. Of the available crop models, QCANE has proven accurate in simulating sugarcane biomass and yield (Liu and Bull, 2001; Liu and Helyar, 2003; O'Leary, 2000). QCANE simulates the effects of water and nitrogen deficits according to the water balance and nitrogen modules adapted from CERES-Maize. QCANE is therefore a suitable model for estimating sugarcane potential yields and yield gaps in SC.

The specific objectives of this study were to (a) evaluate the performance of QCANE model for simulating sugarcane growth, development, and yields under various production levels in SC, (b) to map climatic elements and production levels in SC, (c) to quantify the patterns of on-farm sugarcane yields and yield gaps from 1971 to 2014 in SC, and then to (d) provide a regional framework for increasing sugarcane yields based on yield gaps analysis.

2. Materials and methods

2.1. Study area and climate conditions

The study area was located in SC, including the Guangxi Region and Guangdong, Yunnan, and Hainan Provinces, which together represent a high sugarcane production zone with sophisticated agricultural management. Each province is comprised of several counties, within which are located weather stations. A total of 115 weather stations, operated by the National Meteorological Networks of China Meteorological Administration (CMA), were selected on the basis of proximity to sugarcane planting areas and data availability and integrity from 1970 (45 years) (see Fig. 1). Six of these stations were located at experimental sites where observation data of sugarcane growth, development, and yield were available. These stations were used to calibrate and validate the QCANE model, utilizing available phenology, yield, and climate data (Table A1, Supplementary Information). At these six stations, long term average maximum and minimum temperatures during sugarcane growing season (from planting to harvest) ranged from 24.4 to 30.7 °C and 16.3–23.1 °C respectively. Long term average daily solar radiation at these sites ranged from 10.0 to 18.8 MJ m^{-2} d^{-1}, while total precipitation during sugarcane growing season ranged from 989.8 to 1654.3 mm (Table A2, Supplementary information).

2.2. Data details and pretreatment

Weather data including daily sunshine duration, maximum and minimum temperature, maximum and minimum relative humidity, rainfall, and wind speed from 1970 to 2014 were collected for 115 representative weather stations (Fig. 1). Sunshine duration was converted into daily solar radiation using the Ängström formula (Allen et al., 2005; Ängström, 1924).

Soil data were obtained from the local experiment stations and a soil hydraulic parameters database developed by Dai et al. (2013). The soil data used in QCANE model include the low limit soil water (LL), drained upper limit (DUL), field saturated soil water content (SAT), relative root distribution (RR), organic carbon (OC, derived from the measured amount of soil organic matter divided by the conversion factor of 1.724 according to Wang et al., 2015), the soil bulk density (BD), soil pH (PH), Ammonium-N concentration in dry soil (NH_4), and Nitrate-N concentration in dry soil (NO_3) in six soil layers. One soil type per weather station was selected for the simulation of potential yields to be representative of the main soil types used for sugarcane growth in the local counties. Soil data used in QCANE for Shatang are shown in Table 1.

Experiment data on sugarcane plant type, phenology (planting, emergence, cane appearance, and harvest dates), plant height, yields, and management practices, such as dates and application amounts of fertilizers, were obtained from the six agricultural meteorological experiment stations. Sugarcane phenological data and yield data used for model calibration and validation are provided in Table A1 (Supplementary information).

Annual county-level yields represent average local on-farm yields (Ya) and reflect the management practices adopted by farmers and climate variations from site-to-site and year-to-year. Therefore, county-level yields were compared with potential yields to estimate the yield gaps of sugarcane in SC. In our study, annual county-level yields and planting area of sugarcane for 171 counties were obtained from two data sources: the county crops database maintained by the Planting Management Department of Ministry of Agriculture of the People's Republic of China; and the provincial statistical yearbook of four provinces from National Bureau of Statistics of China (NBSC). These values were then weighted by planting area of sugarcane to obtain the region-wide SC averages.

2.3. Model description and simulations

2.3.1. Description of the model

There are several main sugarcane simulation models currently in use over the world, including the South African model Canegro (Inman-Bamber, 1995), and two Australian models, AUSCANE and APSIM-Sugarcane (Keating et al., 1999; Wegener et al., 1988). The Canegro model converts intercepted photosynthetically active radiation into gross photosynthate using a conversion efficiency. But the Canegro model does not adequately handle the partitioning of dry matter to sucrose (O'Leary, 2000). In contrast, while the AUSCANE and APSIM-Sugarcane models focus on employing radiation use efficiency (RUE), they remain deficient in handling the biological components involved in the simulation of biomass and sucrose accumulation (Liu and Bull, 2001).

QCANE differs from other sugarcane models in its comprehensive treatment of physiological processes, including canopy development, photosynthesis, respiration, partitioning of the photosynthate, and

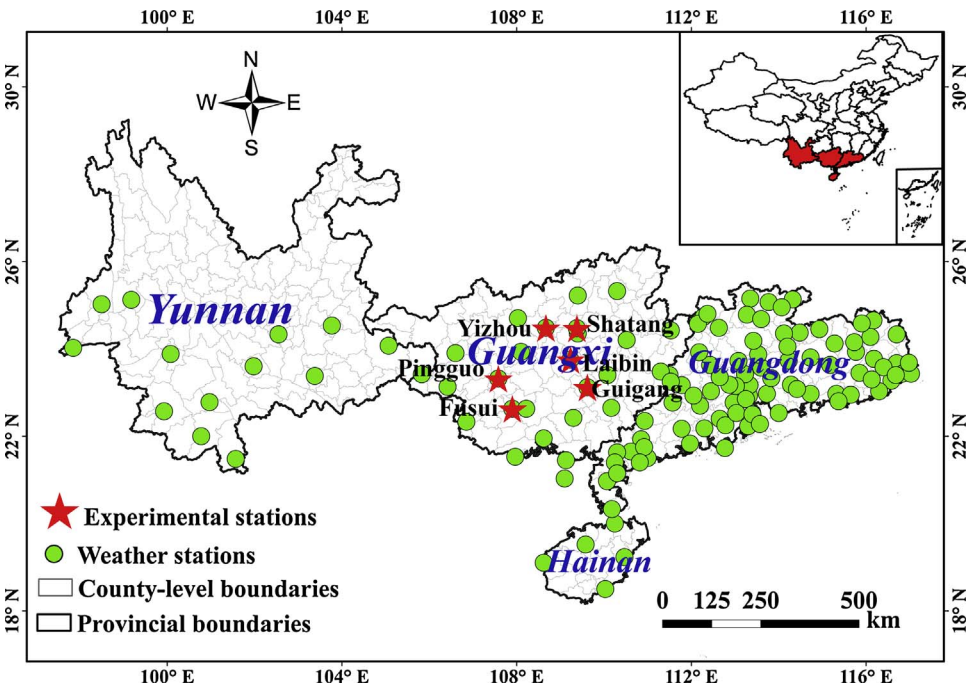

Fig. 1. The locations selected for simulation of sugarcane yield potentials from four provinces in Southern China. Solid circle show locations of weather stations used for simulating yield potentials. Stars indicate locations of experiment stations used for model calibration and validation. Thick lines show province boundaries while fine line show county-level boundaries. Upper-right corner figure is a map of China and location of SC within China.

phenological development (Liu and Bull, 2001). Daily gross CO_2 assimilation by the whole canopy is simulated according to temperature and photosynthetically active radiation interception, which accommodates both light extinction through the canopy and diurnal variation of light-density during the day (Liu, 1996). Respiration is composed of growth respiration and maintenance respiration, with growth respiration set as constant and maintenance respiration determined from temperature and accumulated biomass (Liu and Bull, 2001). By explicitly modelling respiration, QCANE is able to address slowdowns in late stage growth as discussed by Van Heerden et al. (2010). Slowdown occurs in late stages because more photoassimilates produced during the day are required for maintenance respiration, leaving fewer for growth. Partitioning of photoassimilates into vegetative components of sugarcane (leaf, non-millable top, stalk, and root) is done by accounting for temperature, growth stage, and sugar accumulation. Phenological development stages, like emergence and tillering, are controlled by base temperature and thermal time (Liu et al., 1998; Liu and Bull, 2001). The QCANE model has been validated against crop growth in Australian sub-tropical and tropical environments and in a two-year potential experiment with equivalent crop yield over 250 t ha $^{-1}$ in Hawaii (Keating et al., 1995; Liu and Kingston, 1995). The Australian QCANE model also includes water balance and nitrogen sub-modules adapted from CERES-Maize. Hence, it is able to simulate the influence of water and nitrogen stress (Brown, 1987). The water balance module simulates variations of soil water content on a daily time-step to estimate potential yield decrease due to soil water deficits (Ben Nouna et al., 2000; Jones et al., 2003; Popova and Kercheva, 2005; Soler et al., 2007). The nitrogen module simulates soil nitrogen balance processes such as mineralization/immobilization, ammonia volatilization, nitrification, denitrification, and nitrogen leaching (Fosu-Mensah et al., 2012). By taking growth slowdown phenomena into account (Park et al., 2005; Van Heerden et al., 2010), the QCANE model can accommodate the biotic (e.g. crop age), climatic, and physical/chemical (radiation, temperature, water and nutrient) factors that control growth and sucrose accumulation. In addition, QCANE considers row spacing as an input configuration. Crop yield can be influenced indirectly by sugarcane population structure prior to canopy closure, hence, crops with narrow row spacing intercept more radiation than those with wide row spacing, although differences diminish as the crop develops.

2.3.2. Model calibrations and evaluations

All databases required for the QCANE model input, including weather data, soil data, variety data, and management data, were utilized to construct an initial model. Crop parameters in QCANE were calibrated by trial-and-error from the 6 stations of field-measured data including phenology, stalk height, and fresh cane yield of sugarcane in the calibration subsets (Table A1, Supplementary information) (Chen et al., 2010; Liu et al., 2012). Specifically, the thermal parameters of phenological development in sugarcane were calculated using a technique that considers suboptimum and supra-optimum temperature regimes (Liu et al., 1998). The calibrated model was then validated using 14 station-years of data from validation subsets in Table A1 (Supplementary information). For all simulations, only one variety was used across all regions, while irrigation and fertilizer regimes were applied according to actual practices.

To evaluate the accuracy and performance of the QCANE model, the

Table 1
Soil properties of experimental sites at Shatang at depths of 0–120 cm. All soils had a clay loam texture.

Soil depth (cm)	BD (g cm^{-3})	LL (mm mm^{-1})	DUL (mm mm^{-1})	SAT (mm mm^{-1})	RR	OC (g g^{-1})	PH	NH_4 (mg kg^{-1})	NO_3 (mg kg^{-1})
0 – 10	1.43	0.12	0.28	0.35	1.00	2.43	6.75	0.83	4.83
10–20	1.57	0.13	0.29	0.36	0.78	2.27	6.57	0.43	4.17
20–30	1.60	0.13	0.31	0.38	0.77	1.60	6.34	0.32	4.30
30–45	1.72	0.12	0.33	0.38	0.73	0.60	6.20	0.30	4.20
45–60	1.72	0.12	0.33	0.39	0.72	0.55	6.07	0.33	4.20
60–90	1.73	0.13	0.38	0.41	0.69	0.37	5.70	0.30	4.07
90–120	1.79	0.13	0.38	0.40	0.68	0.32	5.50	0.29	3.57

statistical indicators of root mean square error (RMSE), normalized root mean square error (NRMSE), Willmott's index of agreement (D-value, Willmott, 1982), and the coefficient of determination (R^2) were calculated from simulated and observed variables. The values of RMSE and NRMSE reflect the absolute error and relative error between simulated and observed variables respectively, where smaller values indicate better consistency between simulated and observed variables. Whereas R^2 values lie between 0 and 1 and describe how much of the observed dispersion is explained by the prediction, the model can remain biased even when R^2 approaches 1. To account for this, Willmot's systematic RMSE was used (Willmott, 1981).

2.3.3. Long-term simulations for yield gap analysis

After validation, successive simulations of long-term (1971–2014) sugarcane yields were conducted for the 115 weather stations under four conditions: potential (no water and nitrogen stress), water-limited (no nitrogen stress but water stress), nitrogen-limited (no water stress but nitrogen stress), and water-and-nitrogen limited (co-limitation of water and nitrogen). The corresponding yield levels were defined as potential yield (*Yp*, the yield simulated with water applications and nitrogen inputs set as non-limiting), water-limited yield (*Yw*, the yield simulated with the most appropriate nitrogen level, but no irrigation), nitrogen-limited yield (*Yn*, the yield achieved with an ample supply of water, but no nitrogen fertilization), and water and nitrogen co-limited yield (*Ywn*, the yield simulated under the co-limitation of water and nitrogen condition). When no nitrogen is applied, yield will be determined by the amount of mineral N present in the soil and by the amount mineralized from organic matter.

Based on the average of actual sowing and harvest dates from the experimental stations, the simulated crop was sown on 21 Dec and harvested on 20 Dec in the following year. In this study, a single sugarcane variety (Australian sugarcane variety Q141 was used as an alternative of ROC22, as is widely introduced in sugarcane planting areas of China) was utilized at all sites, ignoring the potential for varietal changes over time. To remove the influence of factors other than irrigation and nitrogen, the same row space (1 m) and other management details were fixed in all long-term simulations.

2.4. Data analysis

2.4.1. Calculating yield gaps

On-farm yield (*Ya*) was defined as the average yield observed at a given location. In SC, most sugarcane is cultivated in barren and hilly arid areas with no irrigation, meaning that *Ya* is restricted by both water and fertilizer (Xian et al., 2014). We can therefore define the yield gaps (*YG*) according to sugarcane yield constraint factors:

Yield gap due to water limitation:

$$YGw = Yp\text{-}Yw \tag{1}$$

$$YGw\ \text{percentage} = 100 \times (Yp\text{-}Yw)/Yp \tag{2}$$

Yield gap due to nitrogen limitation:

$$YGn = Yp\text{-}Yn \tag{3}$$

$$YGn\ \text{percentage} = 100 \times (Yp\text{-}Yn)/Yp \tag{4}$$

Total yield gap:

$$YGt = Yp\text{-}Ya \tag{5}$$

$$YGt\ \text{percentage} = 100 \times (Yp\text{-}Ya)/Yp \tag{6}$$

Yield gap due to other factors:

$$YGo = Ywn\text{-}Ya \tag{7}$$

$$YGo\ \text{percentage} = 100 \times (Ywn\text{-}Ya)/Ywn \tag{8}$$

The *YGw*, *YGn*, and *YGt* percentages (a value from 0 to 100%) indicate how close *Yw*, *Yn*, and *Ya* are to the potential yield, respectively. Similarly, *YGo* percentage (0 ~ 100%) indicates how close *Ya* is to the water-and-nitrogen limited yield.

To obtain county-level yield gaps, *Yp*, *Yw*, *Yn*, and *Ywn* at the county level were estimated by interpolation of simulation results from all stations from 1971 to 2014 using ArcGIS 10.2. To do this, simulated values for *Yp*, *Yw*, *Yn*, and *Ywn* at the 115 weather stations were spatially interpolated and rasterized using the ordinary IDW (inverse distance weighting) for each year (Li et al., 2014). Annual county yields for *Yp*, *Yw*, *Yn*, and *Ywn* were then calculated using the tool/command of "zonal statistics as table".

2.4.2. Geospatial patterns of meteorological variables, crop yields, and yield gaps

For each site-year simulation, mean values for the following meteorological variables throughout sugarcane growing season were calculated: daily maximum temperature (*Tmax*), daily minimum temperature (*Tmin*), daily solar radiation (*Rad*), and total precipitation (*P*). After interpolation, the 45-year mean values at each county were then plotted against longitude and latitude to identify major geospatial gradients (Grassini et al., 2009; Liu et al., 2012). Linear regression or second-order polynomial functions were fitted. The climatic elements at each location were weighted by planting area of sugarcane to obtain the region-wide averages for each year (Liu et al., 2012; Sacks and Kucharik, 2011) and linear regression analysis used to detect trends. The slope of the linear regression line against time was evaluated using Student's *t*-test at 95% or 99% confidence intervals. A similar analysis was also executed to identify geospatial gradients of yields and yield gaps at all levels. In addition, the spatial and temporal variation coefficients were also used to analyze the spatial and temporal volatility of climatic elements, yields, and yield gaps. The higher the values of variation coefficients, the greater the volatility (Li et al., 2012). By using the definitions of yield trend pattern categories (i.e. yields decline, yields never improved, yields increasing), further analysis was applied to classify the on-farm yields patterns in each county (Li et al., 2014; Ray et al., 2012).

To identify the most important climatic factors to the spatial variations in potential yield, stepwise multilinear regression analysis (SMLR) and partial correlation analysis were applied to quantify the contributions of climatic elements to changes in sugarcane potential yields in SC for the period 1971–2014. For the SMLR, contributing variables were entered at statistical significance of $P < 0.05$, that is, 95% significant level. All variables with different units were standardized to easily compare the contributions of different variables.

3. Results

3.1. Calibration and validation of the QCANE model

Evaluation of the QCANE model using the experiment data collected at 6 stations (Table A1, Supplementary information) indicated that the model predicted growth stages and yield reasonably well. The R^2 values from simulated and observed days for emergence, cane appearance, and yield were 0.99, 0.99, and 0.98, respectively, whereas the NRMSE were 0.81%, 0.53%, and 3.13%, respectively.

Validation of the simulation model using field observations for 14 station-years (Fig. 2) determined that average simulated emergence after crop start for plant and ratoon crop were 36 (observed 35) and 130 (observed 134) days, respectively. The average simulated cane appearance days after crop start for plant and ratoon crop were 112 and 211, respectively. Both the R^2 values and the D-values for the simulated days from crop start to emergence and cane appearance were higher than 0.98, and the values of NRMSE were 5.7% and 1.9%, respectively (Fig. 2a and b), indicating good agreement between the simulated and observed values. These results indicate that the QCANE model was able to adequately simulate sugarcane growth stages in SC. Furthermore, simulations of stalk height also agreed well with the observations (R^2

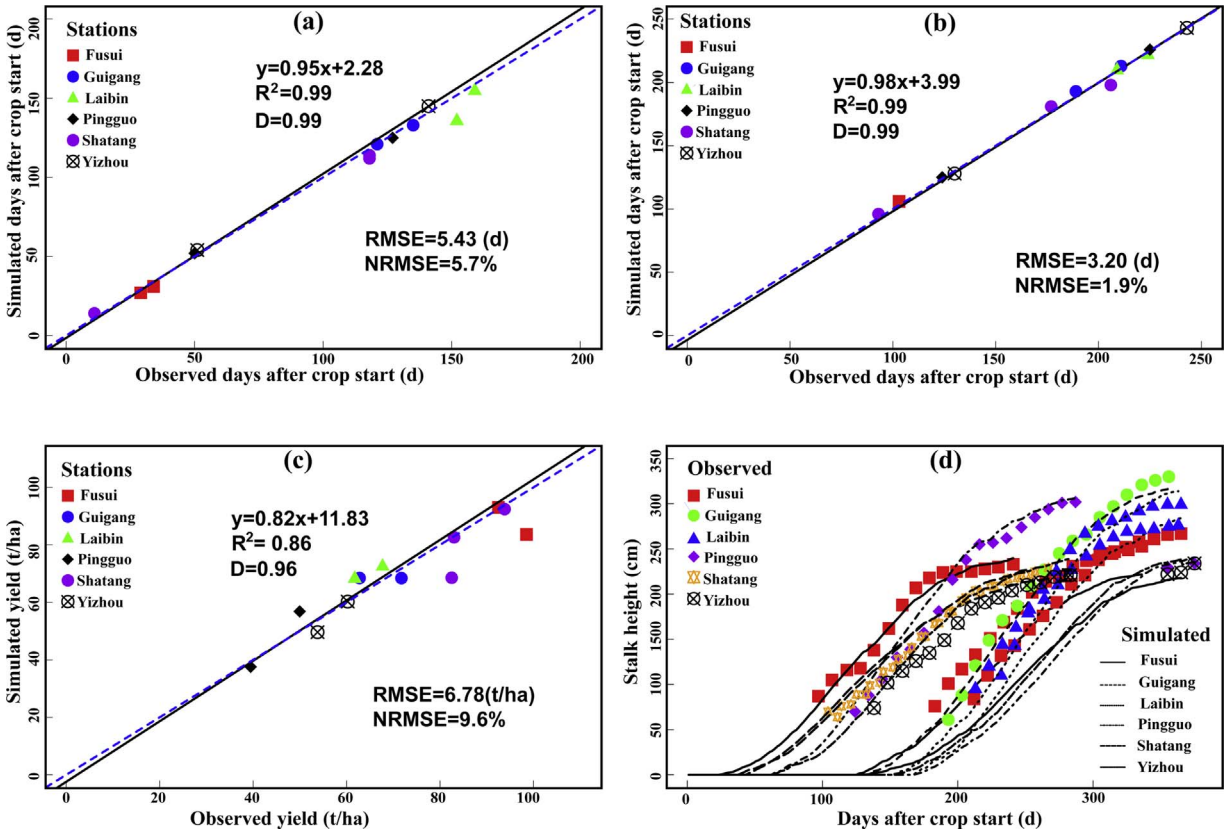

Fig. 2. Comparison of simulated and observed emergence days after crop start (a), cane appearance days after crop start (b), yield (c), and stalk height (d). Yield for QCANE model evaluation and all other simulations in this article are fresh weight. The solid line and dashed line in a, b, and c were regression trend line and 1:1 line, respectively.

values ≥ 0.96, D-value ≥ 0.86) (Fig. 2d), while the simulated yields (Fig. 2c) matched favorably with observed yields (R^2 values 0.86 and D values 0.96, respectively). Overall, the QCANE model estimated sugarcane growth well.

3.2. Spatial and temporal trends of climate variables

The mean minimum temperature for the entire sugarcane growing season (planting to harvest) during the period of study (45 years) was closely correlated with longitude and latitude ($P < 0.01$), ranging from 11.36 °C in Yunnan province to 22.25 °C in Hainan province (Fig. 3a). Likewise, the mean maximum temperature for the entire growing season was significantly correlated with latitude ($R^2 = 0.67$), ranging from 21.63 °C to 29.88 °C in the south (Fig. 3c). Mean solar radiation was significantly correlated with longitude ($R^2 = 0.72$) and latitude ($P < 0.01$), decreasing as longitude and latitude increased: peaking at 99°E in Yunnan province at a maximum value of 23.51 MJ m^{-2} d^{-1}, then decreasing to 10.34 MJ m^{-2} d^{-1} in Guangdong province (Fig. 3e). The long-term mean total precipitation for the sugarcane growing season was positively correlated with longitude ($R^2 = 0.54$), ranging from 840.2 mm in Yunnan province to 2602.82 mm in the southern Guangxi province (Fig. 3g).

Averaged across SC, annual minimum and maximum temperatures for the sugarcane growing season increased over the study period, increasing at 0.32 and 0.21 °C per decade, respectively, from 1970 to 2014 ($P < 0.01$) (Fig. 3b and d). Among the provinces, Yunnan province exhibited the greatest temperature shift. Solar radiation during the sugarcane growing season across SC decreased 0.12 MJ m^{-2} d^{-1} per decade from 1970 to 2014 ($P < 0.01$) (Fig. 3f). However, in southwestern Yunnan and northeastern Guangdong provinces, solar radiation was observed to increase. Total precipitation during the sugarcane growing season decreased 43.73 mm per decade from 1970 to 2014 (Fig. 3h). Although not significant, considerable annual variation was observed over the past 45 years, ranging between ~2000 mm and ~1200 mm across SC. Increasing trends in total precipitation were observed in Hainan province, western Guangxi region, and western Yunnan province (Fig. 3h).

3.3. Simulated potential yields

Simulated means for weighted *Yp*, *Yw*, *Yn*, and *Ywn* were 212.74 t ha^{-1}, 180.11 t ha^{-1}, 109.49 t ha^{-1}, and 82.81 t ha^{-1}, averaged between 1971 and 2014. Temporal variation, as indicated by the coefficient of variation in time (CVt), was 3.55%, 4.63%, 3.68%, and 8.71%, respectively (Table 2). Across SC, mean simulated potential yields ranged from 132.29 t ha^{-1} to 260 t ha^{-1} (Fig. 4a), and mean simulated water-limited yields from 1971 to 2014 ranged from 122.81 t ha^{-1} to 215.87 t ha^{-1} (Fig. 4c). However, nitrogen-limited and water-and-nitrogen limited yields were much lower, ranging from 72.02 t ha^{-1} and 40.4 t ha^{-1} to 140.6 t ha^{-1} and 124.08 t ha^{-1} (Fig. 4e and g), respectively.

Further analysis indicated that the simulated potential yields decreased with increasing longitude and latitude (Fig. 4a). The spatial distribution of potential yields was primarily determined by solar radiation and maximum temperature (Table 3). Average water-limited yields increased with longitude as precipitation increased, peaking at 110.3°E, then decreased with lower maximum temperatures (Fig. 4c and Table 3). Average water-limited yields also decreased with latitude as precipitation decreased during the sugarcane growth period (Fig. 4c and Table 3). Nitrogen-limited yields significantly decreased with increasing longitude and latitude (Fig. 4e). The spatial distribution of nitrogen-limited yields was mainly driven by solar radiation (Table 3). Water-and-nitrogen limited yields were positively correlated with longitude but negatively correlated with latitude (Fig. 4g), driven by

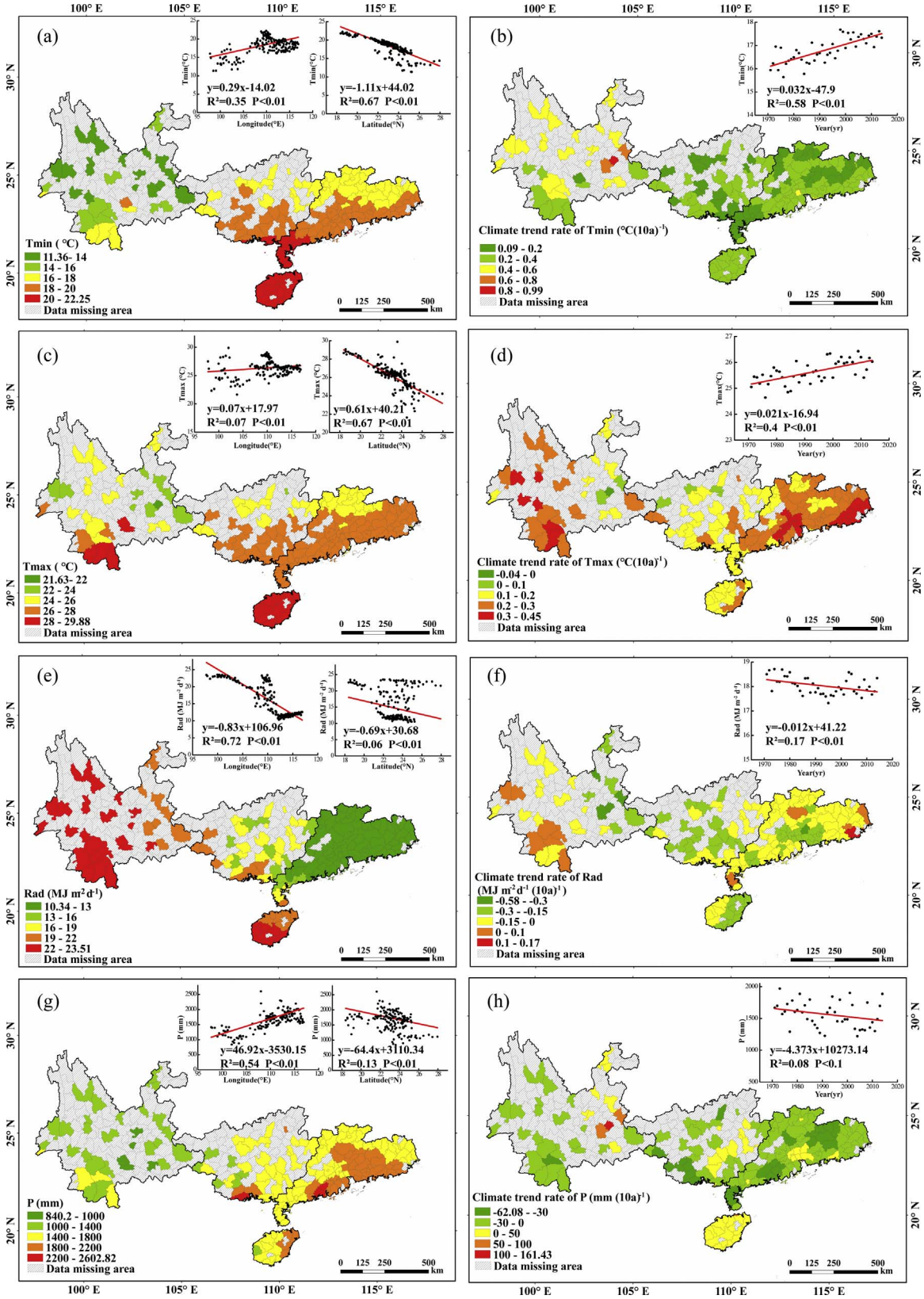

Fig. 3. Distribution of long-term mean minimum temperature (*Tmin*, a), maximum temperature (*Tmax*, c), solar radiation (*Rad*, e), total precipitation (*P*, g), and their climate trend rates (b, d, f, and h) during the growing season of sugarcane in SC. The linear regression curves and equations are shown in each embedded figure.

the spatial distribution of maximum temperature (Table 3).

Potential yields and nitrogen-limited yields increased by 0.043 t ha^{-1} and 0.01 t ha^{-1} per year from 1971 to 2014, respectively, ranging from −0.97 t ha^{-1} yr^{-1} and −0.325 t ha^{-1} yr^{-1} to 1.02 and 1.077 t ha^{-1} yr^{-1} over the 115 weather stations (Fig. 4b and f). However, water-limited yields and water-and-nitrogen limited yields

Table 2
The minimum, maximum, and mean values of 44-year mean simulated potential yields (*Yp*), water-limited yields (*Yw*), nitrogen-limited yields (*Yn*), and water-and-nitrogen-limited yields (*Ywn*) of sugarcane among selected locations in SC. Mean value is the weighted area average based on the sugarcane planting area at the location.

Item	Yp (t ha^{-1})	Yw (t ha^{-1})	Yn (t ha^{-1})	Ywn (t ha^{-1})
Minimum	132.29	122.81	72.02	40.40
Maximum	260.00	215.87	140.60	124.08
Mean	212.74	180.11	109.49	82.81
CVt (%)	3.55	4.63	3.68	8.71
CVs (%)	16.25	11.62	12.83	16.49

CVs: spatial coefficient of variability; CVt: time coefficient of variability.

decreased by 0.059 t ha^{-1} yr^{-1} and −0.088 t ha^{-1} yr^{-1}, respectively, with the range of −0.748 t ha^{-1} yr^{-1} and −0.424 t ha^{-1} yr^{-1} to 1.98 t ha^{-1} yr^{-1}and 0.376 t ha^{-1} yr^{-1} among 115 weather stations (Fig. 4d and h). Stations with greatest growth in potential yield were mainly distributed in the southwestern Yunnan province (Fig. 4b). However, potential yields in the other three provinces primarily exhibited downward trends (Fig. 4b).

3.4. On-farm yields

The regional weighted average for on-farm sugarcane yield was 56.44 t ha^{-1} from 1971 to 2014, ranging between 13.81 t ha^{-1} and 115.11 t ha^{-1} (Fig. 5a). In 58% of the sugarcane areas, yields were below 60 t ha^{-1}, congregated in the areas of Hainan, Guangxi and Yunnan provinces, and the northeastern Guangdong province (Fig. 5a). Nearly 36% of the sugarcane area yields were between 60 t ha^{-1} and 80 t ha^{-1} (Fig. 5a). High yield areas (above 80 t ha^{-1}) were predominantly located in the central and eastern Guangdong province, and Dali, Mile of Yunnan province. On the whole, the current productivity of sugarcane in SC was higher in central and eastern areas, compared to northern and southern areas (Fig. 5a).

The on-farm sugarcane yields increased by 1.276 t ha^{-1} per year from 1971 to 2014, ranging from −3.824 t ha^{-1} yr^{-1} to 3.874 t ha^{-1} yr^{-1} at the county level (Fig. 5b). While the growth rate in on-farm yields was remarkable throughout the period, we found that about 26% of sugarcane areas, predominantly the central Yunnan and northern Guangdong provinces, witnessed declining growth, while 4.6% of sugarcane areas yields remained stable (Fig. 5c).

3.5. Yield gaps

Over SC, the regional weighted average total yield gap (*YGt*) was 156.3 t ha^{-1}, about 73% of potential yield (Table 4). Among our study counties, the long-term mean *YGt* varied from 74.82 t ha^{-1} (43%) to 214.2 t ha^{-1} (93%), depending on climate conditions and crop management practices (Fig. 6a and b). In 32% of the sugarcane areas, mainly in most areas of Hainan and Yunnan provinces, as well as the southern Guangxi Region, *YGt* was more than 160 t ha^{-1} (75%). For about 36% of sugarcane areas, *YGt* was between 130 t ha^{-1} (about 60%) and 160 t ha^{-1}, while the remainder, mostly in Guangdong province, had *YGt* values less than 130 t ha^{-1} (60%) (Fig. 6a and b). Total yield gaps were greatly influenced by the spatial distribution of on-farm yields of a region. Variation in the total yield gap was negatively correlated with on-farm yields (Fig. 7a, R^2 = 0.68). Total yield gap decreased considerably by 1.259 t ha^{-1} per year from 1971 to 2014, ranging from −8.623 t ha^{-1} yr^{-1} to 3.967 t ha^{-1} yr^{-1} across SC (Fig. 6c). Temporal trends in total yield gap were mainly determined by the on-farm yield patterns (Fig. 7b, R^2 = 0.61).

Averaged across SC, mean yield loss due to water deficiency (potential yields minus water-limited yields, *YGw*) was 32.25 t ha^{-1}, about 15% of potential yield (Table 4). Among study counties, *YGw* varied from 6.37 t ha^{-1} (4%) to 80.94 t ha^{-1} (33%), depending on county-specific precipitation rates (Fig. 6d and e). In 14% of sugarcane areas, mainly in the eastern Yunnan province, *YGw* was more than 50 t ha^{-1} (23%). In contrast, for 63% of the sugarcane areas, mostly in Guangdong, Guangxi, and Hainan provinces, which had higher total precipitation rates, *YGw* was less than 35 t ha^{-1} (16%) (Fig. 6d and e). *YGw* was significantly negatively correlated with spatial variation in total precipitation. *YGw* was lower in counties with high total precipitation, and increased considerably in counties where total precipitation was lower (Fig. 3d and 6b). The yield gap due to water deficiency increased by 0.1 t ha^{-1} per year from 1971 to 2014, varying from −1.743 t ha^{-1} yr^{-1} to 0.577 t ha^{-1} yr^{-1} across SC (Fig. 6f). However, inter-annual precipitation variability was reflected in a large temporal variation coefficient of 24.04% for *YGw* (Table 4).

Across SC, the mean value of yield loss due to nitrogen deficiency (potential yields minus nitrogen-limited yields, *YGn*) was 101.3 t ha^{-1}, about 48% of potential yield, ranging from 60.8 t ha^{-1} (38%) to 146.11 t ha^{-1} (58%) among study counties (Fig. 6g and h). In 61% of the sugarcane areas, mainly in Guangdong province, which had lower solar radiation, *YGn* was less than 100 t ha^{-1} (47%). While in 10% of the sugarcane areas, mainly in the central Guangxi region and the eastern Yunnan province, *YGn* was more than 115 t ha^{-1} (54%) (Fig. 6g and h). The yield gap due to nitrogen deficiency increased by 0.04 t ha^{-1} per year from 1971 to 2014. Linear trends ranged from −0.919 t ha^{-1} yr^{-1} to 0.734 t ha^{-1} yr^{-1} among the study counties (Fig. 6i).

Averaged over SC, the yield gap between water-and-nitrogen limited yields and on-farm yields (*YGo*) was 29.19 t ha^{-1} (Table 4). As both *Ywn* and *Ya* are water-and-nitrogen limited, the yield loss must be due to other factors, such as, cultivar choice, management of diseases, pests, weeds, mechanization, and policy direction. In the northern and central counties of Guangdong province, and in Dali, Lijiang, Mile of Yunnan province, on-farm yields were slightly higher than water-and-nitrogen limited yields because of the utilization of irrigation and fertilizer. Among the study counties, *YGo* ranged from −18.38 t ha^{-1} to 66.11 t ha^{-1} (Fig. 6j), with large spatial variations (68%). The highest *YGo* areas were mainly in the eastern Yunnan province, where the largest yield increases could be achieved by utilizing none water-and-nitrogen practices. Spatial patterns in *YGo* were negatively correlated with on-farm yields (Fig. 7c, R^2 = 0.97), while the temporal trends of *YGo* were mainly determined by the on-farm yield trends (Fig. 7d, R^2 = 0.73). The yield gap associated with other factors than water and nitrogen decreased by 1.272 t ha^{-1} per year, as on-farm yields increased. Linear trends ranged from −7.934 t ha^{-1} yr^{-1} to 7.6 t ha^{-1} yr^{-1} across SC (l), due mainly to differences in socioeconomic conditions, such as mechanization of sugarcane production, adoption of new technologies, and effects from other investments.

4. Discussion

Validation of the QCANE model indicated that simulated growth and development of sugarcane in SC was consistent and corresponded well with observed values. Long-term average potential yields of sugarcane in SC varied spatially from 132.29 t ha^{-1} to 260 t ha^{-1}, while the weighted average was 212.74 t ha^{-1} for the entire region. Mean potential yields from this study were similar to those of other studies based on other crop models or water availability experiments. For example, The sugarcane potential yield estimated by Agroecological Zone Model in southern Brazil ranged from 180 to 200 t ha^{-1} (Monteiro and Sentelhas, 2014), while the potential yield estimated by a simple agrometeorological model in the Northeastern region of Brazil ranged

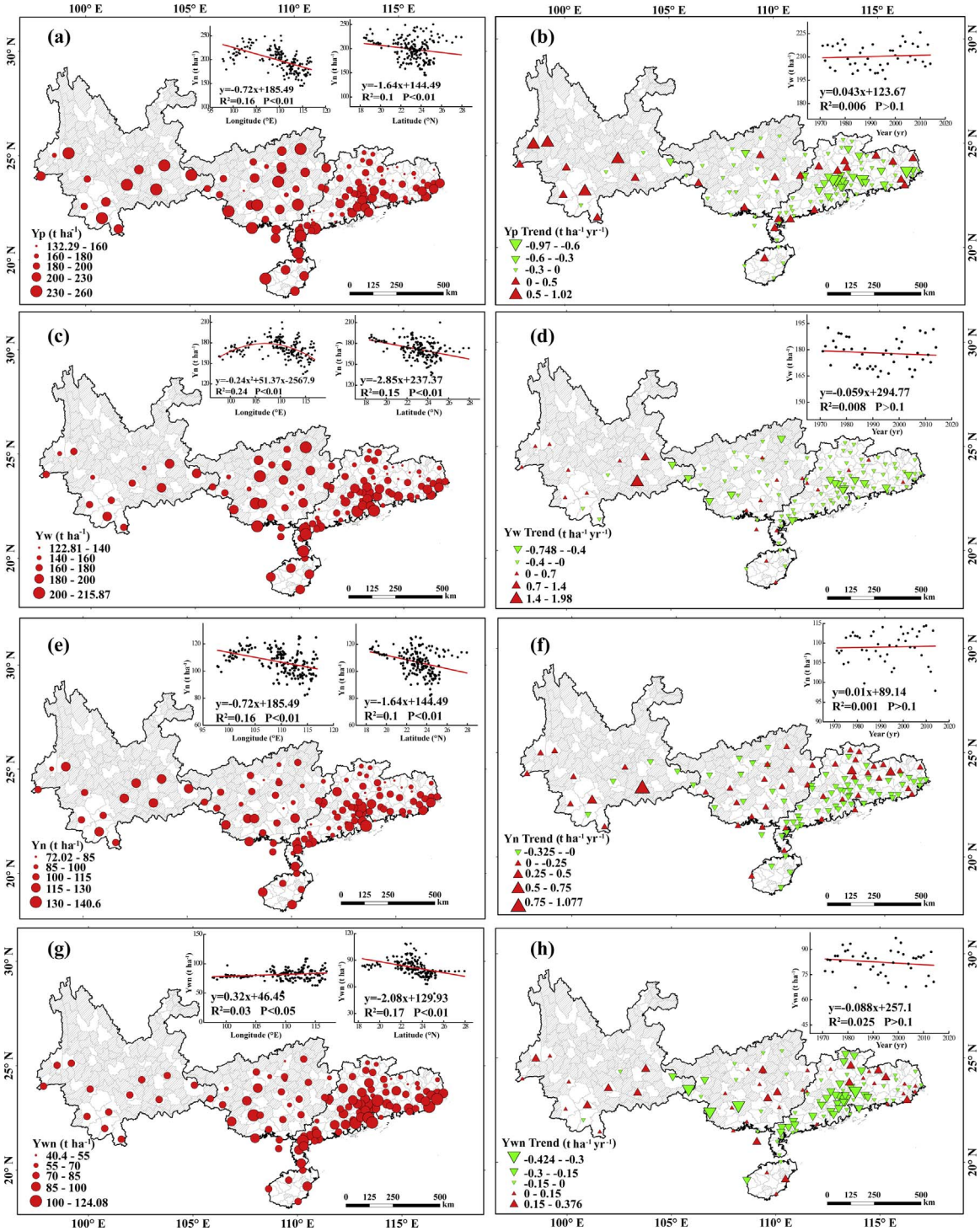

Fig. 4. Spatial distribution and linear trends of long-term mean simulated potential yield (a and b), water-limited yield (c and d), nitrogen-limited yield (e and f), water-and-nitrogen limited yield (g and h) averaged over 1971–2014 among selected weather stations. The size of the circle and triangle is proportional to the average yields, and the upward triangle indicates increasing trend while the downward triangle indicates decreasing trend.

from 68.5 to 232.7 t ha^{-1} (Monteiro and Sentelhas, 2017). In addition, Balasaheb (2013) obtained 210 t ha^{-1} of the sugarcane planting type adsali under optimum experimental conditions in the research station of Maharashtra. Coelho et al. (2015) obtained an average potential yield of 232.2 t ha^{-1} for different varieties under full drip irrigation at "Luiz de Queiroz" College of Agriculture (USP) in Piracicaba-SP. These results indicated that our simulated potential yields were reliable.

Spatial patterns in potential yields were mainly driven by solar radiation and temperature, with solar radiation decreasing from west to east, and temperature decreasing as latitude increased. Our modelling indicated that potential yields decreased from west to east and from south to north because of lower radiation and less tillering caused by

Table 3
Influences of climate factors on yield potentials of sugarcane in SC.

Item	Correlation coefficient				Fitting formula	R^2
	Tmin	Tmax	Rad	P		
Yp	−0.11	0.54**	0.43*	0.01	Y = −77.14 + 6.83Tmax + 6.02Rad	0.39
Yw	−0.03	0.35*	0.28	0.54**	Y = 19.41 + 0.02P + 4.58Tmax	0.34
Yn	0.16	0.30	0.41**	−0.26	Y = 46.84 + 3.36Rad	0.16
Ywn	−0.11	0.34*	0.12	0.17	Y = −50.55 + 5.09Tmax	0.12

* Significant at $P < 0.05$.
** Significant at $P < 0.01$.

lower temperatures. The finding is typical of crops that require high temperatures. For example, Welch et al. (2010) found that higher maximum temperatures raised rice yield in tropical/subtropical Asia. In Brazil, Marin et al. (2013) found that the stalk fresh mass of sugarcane responded positively to an increase in air temperature up to 6 °C, decreasing from then on. In addition, Marin (2012) found that solar radiation was the most important climate factor affecting sugarcane potential yields.

The on-farm yields have been developing rapidly due to the adaptation of high-yield varieties, introduction of high-yield management practices, and changing agricultural production polices (Li, 2004). Nevertheless, growth in yields have either stagnated, or even decreased, in central Yunnan and northern Guangdong provinces. One explanation is the decrease in precipitation observed in these sugarcane growing areas (Fig. 3h), as well as the high frequency of drought (Li and Wei, 2006). Another explanation is that transportation costs are high and mechanization adaptation has been slow in these regions (Li and Yang, 2015). Uncertainty around financial rewards for farmers and producers has also stymied investment (Li and Wei, 2006). Hence, a comprehensive consideration of sugarcane production and yield potential should be prioritized by policy makers.

The yield gap between potential yield and on-farm yield in SC is about 73% of potential yield, which was higher than the results of yield gaps in other countries like Brazil, India, and South Africa. For instance, the total yield gap, as a percentage of potential yield, ranges from 42.95% to 45.28% for different planting types of sugarcane in Maharashtra, as was estimated under different field situations by Balasaheb (2013). Van den Berg and Singels (2013) indicated that the yield gap between water-limited yield (simulated by the Canesim model) and actual yield for small-scale sugarcane farmers in South Africa was 53%. Marin et al. (2016) found that the magnitude of the yield gap between water-limited yield (134 t ha^{-1}, simulated by the DSSAT/CANEGRO model) and actual yield (82 t ha^{-1}) for sugarcane in Brazil was only 38% of water-limited yield. The reasons for the larger yield gap in SC mainly lie in the lower on-farm yields caused by the low

Table 4
The variation of 44-year total yield gap (*YGt*), yield gap due to water and nitrogen (*YGwn*), yield gap due to nitrogen (*YGn*), yield gap due to water (*YGw*), and yield gap due to other factors (*YGo*) of sugarcane among study counties in the SC. Mean value is the weighted area average based on the sugarcane planting area at the location.

Item	YGt (t ha^{-1}) (%)	YGw (t ha^{-1}) (%)	YGn (t ha^{-1}) (%)	YGo (t ha^{-1}) (%)
Minimum	74.82 (43%)	6.37 (4%)	60.8 (38%)	−18.38 (-23%)
Maximum	214.2(93%)	80.94 (33%)	146.11 (58%)	66.11 (83%)
Mean	156.3(73%)	32.25(15%)	101.3(48%)	29.19(35%)
Trend	−1.259**	0.1	0.04	−1.272**
CVs (%)	19.80	59.30	17.96	68.01
CVt (%)	12.42	24.04	5.11	65.06

*Significant at $P < 0.05$.
** Significant at $P < 0.01$.

level of mechanization, intensification, and no access to irrigation (Li and Wei, 2006; Wegener et al., 1999).

Yield losses caused by water limitation averaged across SC were 15% of the potential yield, with large spatial variation coefficient. The largest values of *YGw* occurred in Yunnan province, due to low precipitation rates (Fig. 3g). Moreover, the yield gap due to water limitation varied temporally because of inter-annual precipitation. For example, *YGw* was relatively high (average 23%) in 1992, resulting from drought stress during the stalk elongation stage.

The yield gap due to nitrogen deficiency ranged from 38% to 58% when averaged across SC, which was reasonably higher than yield gap caused by water stress. Boling et al. (2010) reported similar results, reporting that the rice yield gap caused by nitrogen stress (35–63%) was higher than yield gap caused by water limitation (4–28%). Sugarcane yield in SC is limited more by nitrogen deficit than water due to the abundant precipitation, indicating that more attention should be paid to fertilization in crop management. However, in our study we used ratoon crops in all simulation scenarios, which increased the effect of nitrogen deficiency on sugarcane yield over time (Wiedenfeld, 1995).

The yield gap caused by factors other than water and nitrogen were largely affected by volatility in on-farm yields. Among SC counties, considerable variation in these yield gaps was driven by inter-annual variation. Importantly, differences between counties were usually higher than the local yield gap between average on-farm yields and potential yields. Hence, to reduce these yield gaps, it is critical to focus on reducing variation among counties and target low yielding farms through cultivar and management improvement, such as weed and pest control, integrated mechanization, and changing the policy direction to subsidize sugarcane production (Beza et al., 2016; Fischer, 2015; He et al., 2015; Sun et al., 2016; Xiao and Tao, 2014).

This study has made a pivotal contribution to better understanding potential yields, yield gaps, and opportunities for increasing sugarcane yields in SC. However, owing to the limited availability of data, the

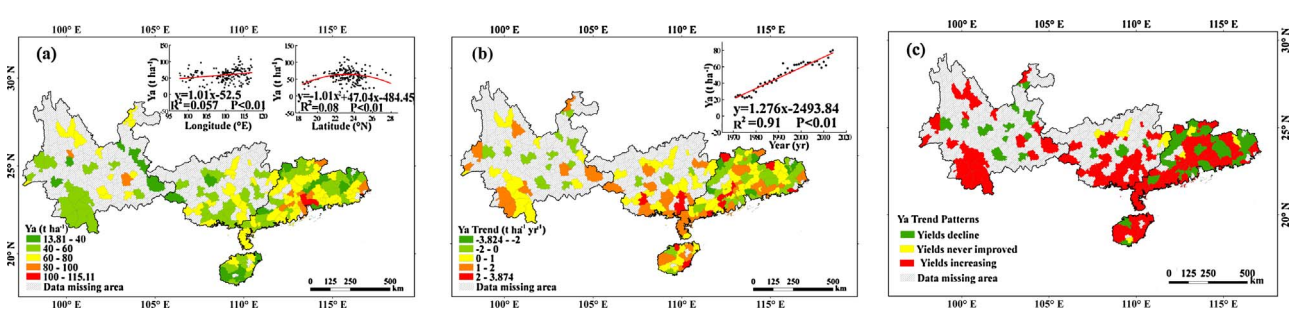

Fig. 5. Mean values (a), linear trend (b), yields trend patterns (c) for on-farm yields of sugarcane at the county level from 1971 to 2014.

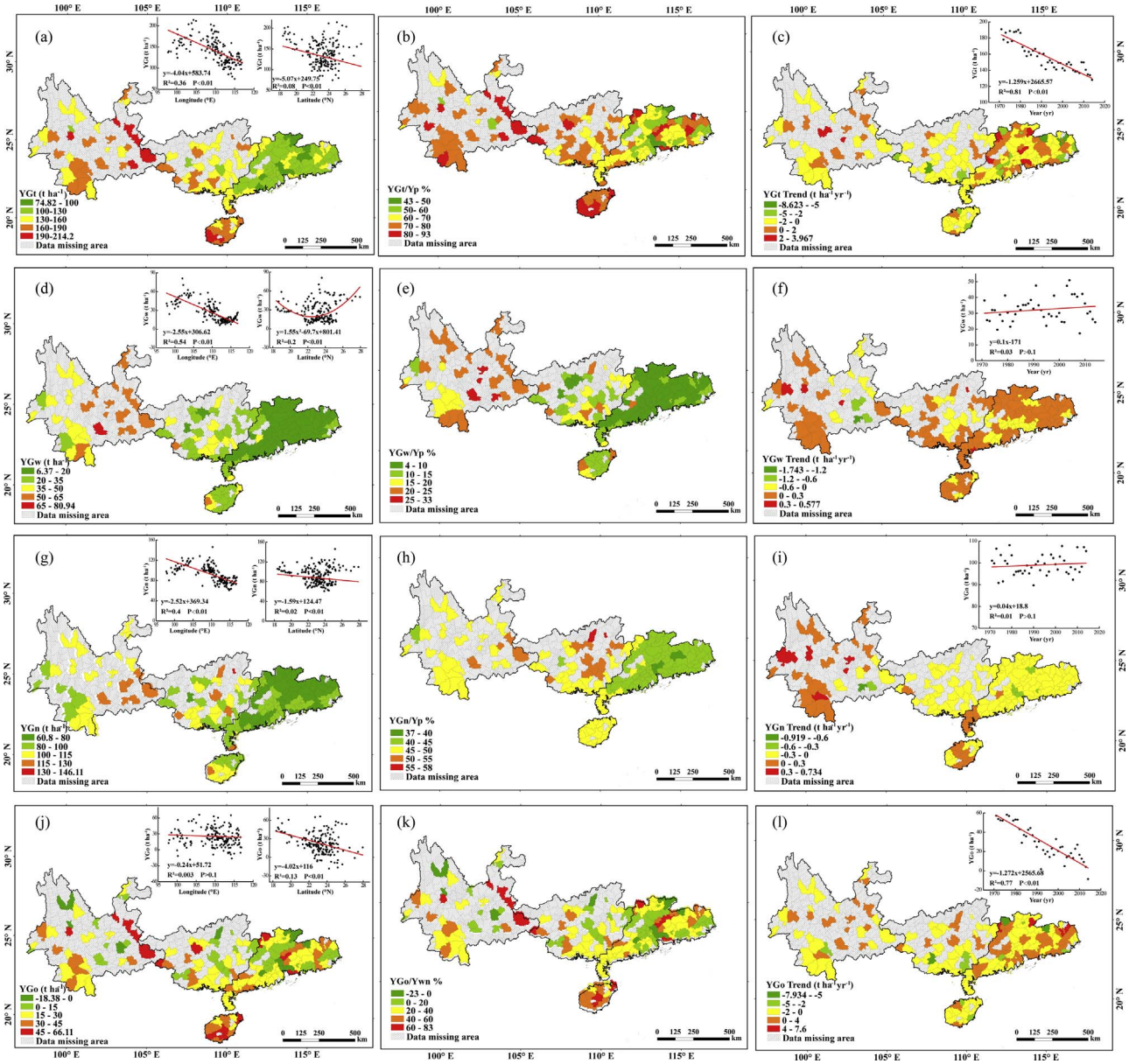

Fig. 6. Spatial distribution of sugarcane yield gaps (a: *YGt*; d: *YGw*; g: *YGn*; j: *YGo*), and their percentage of potential yields (b: *YGt/Yp* %; e: *YGw/Yp* %; h: *YGn/Yp* %; k: *YGo/Ywn* %), as well as their linear trend (c: *YGt* trend; f: *YGw* trend; i: *YGn* trend; l: *YGo* trend) against year in 1971–2014.

QCANE model was calibrated and validated using data from only six experimental stations located in Guangxi Region. Additional validation of the QCANE model with more data from other provinces should prove fruitful and may provide stronger evidence of the ability of the QCANE model to assess sugarcane yield gaps across SC. Moreover, we used the same sugarcane variety for all stations throughout the simulation period, but taking variation in sugarcane varieties into account may achieve a more accurate quantification of potential yields. In addition, the decline in simulated yield may appear over several ratoon crops, which may affect the dynamics of nitrogen requirements during the production of sugarcane biomass and may lead to ratoon stunting disease (Moore et al., 1997). Therefore, more comprehensive and detailed farm data, such as plant type, sowing dates, harvest dates, the date and amount of irrigation and fertilization, as well as on-farm yields and planting areas, could support the validation of results and reveal the constraints causing yield gaps. According to these additional validations, more reliable results could be provided for policymakers to support relevant development strategies to increase sugarcane yields in SC.

5. Conclusions

This study presented quantitative analyses on potential yields and yield gaps of sugarcane and their spatio-temporal variation in SC utilizing crop modeling and GIS-based spatial interpolation. The QCANE model could accurately simulate sugarcane growth, development and yields under potential, water-limited, nitrogen-limited, and water-and-nitrogen limited conditions in SC. The analysis showed a warming trend all over the SC, whereas the overall trends in total precipitation and solar radiation have been declining over the sugarcane growing seasons examined from 1970 to 2014. The spatial distribution of the potential yields was primarily determined by solar radiation and temperature. Large gaps between simulated potential and on-farm yields of sugarcane indicated that there was great potential to increase the

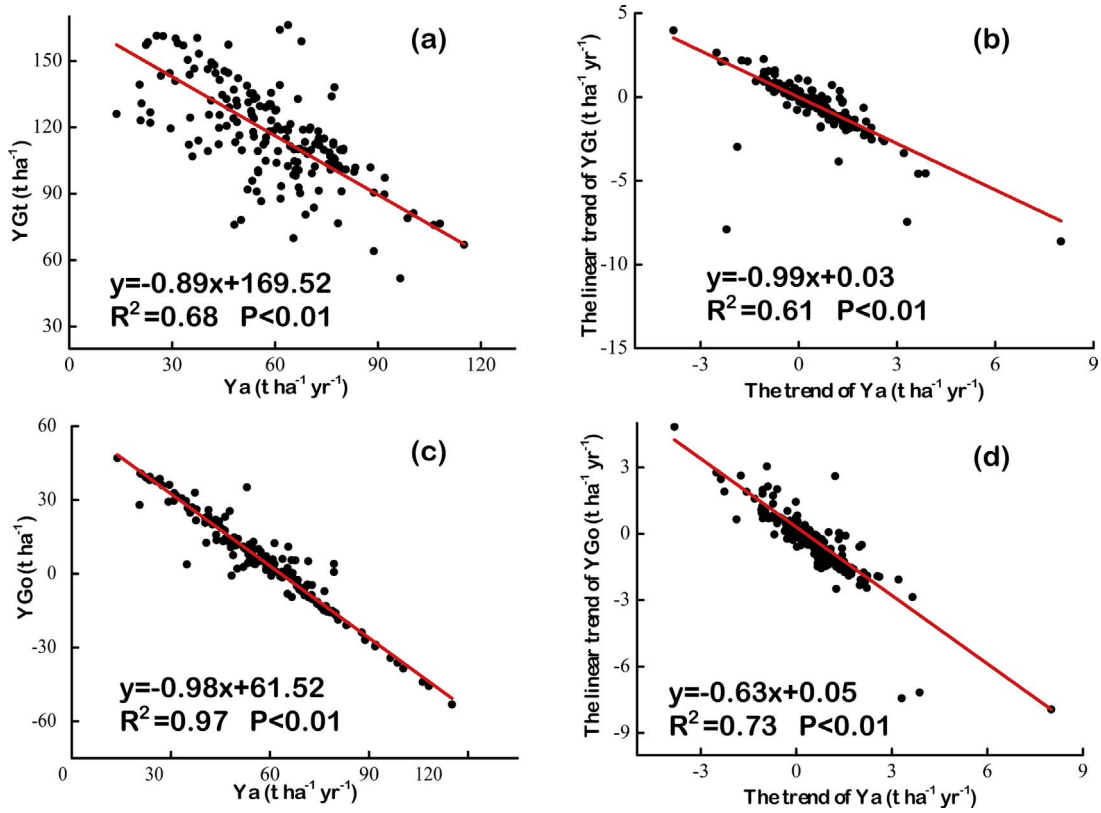

Fig. 7. The relationships between on-farm yield (*Ya*) and total yield gap (*YGt*, a), yield gap due to other factors (*YGo*, c) at the county level from 1971 to 2014, and the relationship between *Ya* linear trend and *YGt* linear trend (b), *YGo* linear trend (d).

sugarcane productivity in SC. Spatial analysis indicated that the largest yield gap caused by water stress was in Yunnan province, due to its lower rate of precipitation. The yield gap caused by water deficiency was lower than the yield gap caused by nitrogen stress, given the generally abundant precipitation in SC. The yield gap caused by factors other than water and nitrogen were largely driven by the variation of on-farm yields, and these yield gaps could be mitigated by improving varietal choice, agrotechnical service provision, government support, and management practices such as proper weed and pest control.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.eja.2017.10.005.

References

Ångström, A., 1924. Solar and terrestrial radiation. Q. J. R. Meteorol. Soc. 50, 121–126.
Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 2005. Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements. FAO (FAO Irrigation and drainage paper No.56).
Balasaheb, Balasaheb, D.T.a I., 2013. Quantification of Yield Gaps in Different Planting Types of Sugarcane in Maharashtra 5. pp. 34–39 (Work. Pap).
Ben Nouna, B., Katerji, N., Mastrorilli, M., 2000. Using the CERES-Maize model in a semi-arid Mediterranean environment: evaluation of model performance. Eur. J. Agron. 13, 309–322.
Beza, E., Silva, J.V., Kooistra, L., Reidsma, P., 2016. Review of yield gap explaining factors and opportunities for alternative data collection approaches. Eur. J. Agron. 1–17.
Boling, A.A., Tuong, T.P., van Keulen, H., Bouman, B.A.M., Suganda, H., Spiertz, J.H.J., 2010. Yield gap of rainfed rice in farmers' fields in Central Java, Indonesia. Agric. Syst. 103, 307–315.
Brown, D.M., 1987. CERES-Maize: a simulation model of maize growth and development. In: In: Jones, C.A., Kiniry, J.R. (Eds.), Agric. For. Meteorol 41. Texas A & M University Press, College Station, TX, pp. 339 pp. + two diskettes. U.S. $33.50 (cloth) 1986, 194.
Casanova, D., Goudriaan, J., Bouma, J., Epema, G.F., 1999. Yield gap analysis in relation to soil properties in direct-seeded flooded rice. Geoderma 91, 191–216.
Chen, C., Wang, E., Yu, Q., 2010. Modelling the effects of climate variability and water management on crop water productivity and water balance in the North China Plain. Agric. Water Manage. 97, 1175–1184.
Coelho, R.D., Barbosa, F. da S., Leal, D.P.V., Santos, L. da C., Junior, E.F.F., Barros, T.H. da S., Lizcano, J.V., Martin, D.L., 2015. Sugarcane Productivity under Drip Irrigation in Brazil: Varieties, Irrigation Depths and Ripening Processes. In: 2015 ASABE Annual International Meeting. ASABE. St. Joseph, Mich. pp. 1. http://dx.doi.org/10.13031/aim.20152188414.
Dai, Y., Shangguan, W., Duan, Q., Liu, B., Fu, S., Niu, G., 2013. Development of a China dataset of soil hydraulic parameters using pedotransfer functions for land surface modeling. J. Hydrometeorol. 14, 869–887.
Evans, L.T., Fisher, R.A., 1999. Yield potential Its definition, measurement, and significance. Crop Sci. 39, 1544–1551.
Fischer, R.A., 2015. Definitions and determination of crop yield, yield gaps, and of rates of change. Field Crop. Res. 182, 9–18.
Fosu-Mensah, B.Y., MacCarthy, D.S., Vlek, P.L.G., Safo, E.Y., 2012. Simulating impact of seasonal climatic variation on the response of maize (Zea mays L.) to inorganic fertilizer in sub-humid Ghana. Nutr. Cycl. Agroecosyst. 94, 255–271.
Grassini, P., Yang, H., Cassman, K.G., 2009. Limits to maize productivity in Western Corn-Belt: a simulation analysis for fully irrigated and rainfed conditions. Agric. For. Meteorol. 149, 1254–1265.
He, L., Asseng, S., Zhao, G., Wu, D., Yang, X., Zhuang, W., Jin, N., Yu, Q., 2015. Impacts of recent climate warming, cultivar changes, and crop management on winter wheat phenology across the Loess Plateau of China. Agric. For. Meteorol. 200, 135–143.
Inman-Bamber, G., 1995. Climate and water constraints to production in the South African Sugar Industry. Proc. South Afr. Sugar Technol. Assoc. 69, 55–59.
Jones, J., Hoogenboom, G., Porter, C., Boote, K., Batchelor, W., Hunt, L., Wilkens, P., Singh, U., Gijsman, A., Ritchie, J., 2003. The DSSAT cropping system model. Eur. J. Agron. 18, 235–265.
Keating, B., Liu, D., Inman-Bamber, N., Robertson, M., Muchow, R., Kingston, G., 1995. Comparison of levels of approach in modelling sugarcane potential yield. Proc. Work Res. Model. Approaches Examine Sugarcane Prod. Oppor. Constraints 43–51.
Keating, B.A., Robertson, M.J., Muchow, R.C., Huth, N.I., 1999. Modelling sugarcane production systems I. Dev. Perform. Sugarcane Module. Field Crop. Res. 61, 253–271.
Li, Y., Wei, Y., 2006. Sugar industry in China:R & d and policy initiatives to meet sugar

and biofuel demand of future. Sugar Tech. 8, 203–216.
Li, Y.R., Yang, L.T., 2015. Sugarcane agriculture and sugar industry in China. Sugar Tech. 17, 1–8.
Li, K., Yang, X., Liu, Y., Xun, X., Liu, Z., Wang, J., Lu, S., Wang, E., 2012. Distribution characteristics of winter wheat yield and its influenced factors in north China. ACTA Agron. Sin. 38, 1483–1493.
Li, K., Yang, X., Liu, Z., Zhang, T., Lu, S., Liu, Y., 2014. Low yield gap of winter wheat in the North China Plain. Eur. J. Agron. 59, 1–12.
Li, Y.R., 2004. China: an emerging sugar super power. Sugar Tech. 6, 213–227.
Liu, D.L., Bull, T.A., 2001. Simulation of biomass and sugar accumulation in sugarcane using a process-based model. Ecol. Modell. 144, 181–211.
Liu, D.L., Helyar, K.R., 2003. Simulation of seasonal stalk water content and fresh weight yield of sugarcane. Field Crop. Res. 82, 59–73.
Liu, D.L., Kingston, G., 1995. QCANE: a simulation model of sugarcane growth and sugar accumulation. Work. Proc. Res. Model. Approaches Assess Sugarcane Prod. Oppor. Constraints 25–29.
Liu, D.L., Kingston, G., Bull, T.A., 1998. A new technique for determining the thermal parameters of phenological development in sugarcane, including suboptimum and supra-optimum temperature regimes. Agric. For. Meteorol. 90, 119–139.
Liu, Z., Yang, X., Hubbard, K.G., Lin, X., 2012. Maize potential yields and yield gaps in the changing climate of northeast China. Glob. Chang. Biol. 18, 3441–3454.
Liu, S., Pu, C., Ren, Y., Zhao, X., Zhao, X., Chen, F., Xiao, X., Zhang, H., 2016a. Yield variation of double-rice in response to climate change in Southern China. Eur. J. Agron. 81, 161–168.
Liu, Z., Yang, X., Lin, X., Hubbard, K.G., Lv, S., Wang, J., 2016b. Maize yield gaps caused by non-controllable, agronomic, and socioeconomic factors in a changing climate of Northeast China. Sci. Total Environ. 541, 756–764.
Liu, D.L., 1996. Incorporating diurnal light variation and canopy light attenuation into analytical equations for calculating daily gross photosynthesis. Ecol. Modell. 93, 175–189.
Lobell, D.B., Ortiz-Monasterio, J.I., 2006. Regional importance of crop yield constraints: linking simulation models and geostatistics to interpret spatial patterns. Ecol. Modell. 196, 173–182.
Lobell, D.B., Cassman, K.G., Field, C.B., 2009. Crop yield gaps: their importance, magnitudes, and causes. Annu. Rev. Environ. Resour. 34, 179–204.
Lu, C., Fan, L., 2013. Winter wheat yield potentials and yield gaps in the North China Plain. Field Crop. Res. 143, 98–105.
Marin, F.R., Jones, J.W., Singels, A., Royce, F., Assad, E.D., Pellegrino, G.Q., Justino, F., 2013. Climate change impacts on sugarcane attainable yield in southern Brazil. Clim. Change 117, 227–239.
Marin, F.R., Martha, G.B., Cassman, K.G., Grassini, P., 2016. Prospects for increasing sugarcane and bioethanol production on existing crop area in Brazil. Bioscience 66, 307–316.
Marin, F.R., 2012. Understanding sugarcane yield gap and bettering crop management through crop production efficiency. Crop Manage. Cases Tools High Yield Sustain 109–118.
Meng, Q., Hou, P., Wu, L., Chen, X., Cui, Z., Zhang, F., 2013. Understanding production potentials and yield gaps in intensive maize production in China. Field Crop. Res. 143, 91–97. http://dx.doi.org/10.1016/j.fcr.2012.09.023.
Monteiro, L.A., Sentelhas, P.C., 2014. Potential and actual sugarcane yields in southern Brazil as a function of climate conditions and crop management. Sugar Tech. 16, 264–276. http://dx.doi.org/10.1007/s12355-013-0275-0.
Monteiro, L.A., Sentelhas, P.C., 2017. Sugarcane yield gap: can it be determined at national level with a simple agrometeorological model? Crop Pasture Sci. 68, 272–284. http://dx.doi.org/10.1071/CP16334.
Moore, P.H., Botha, F.C., Furbank, R.T., 1997. Potential for overcoming physio-chemical limits to sucrose accumulation. Bone Joint J. 49, 135–137.
Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., Foley, J. a., 2012. Closing yield gaps through nutrient and water management. Nature 490, 254–257.
National Bureau of Statistics of China (NBSC), 2014. China Statistics Yearbook. China Statistics Press, Beijing.
O'Leary, G.J., 2000. A review of three sugarcane simulation models with respect to their prediction of sucrose yield. Field Crop. Res. 68, 97–111.
Park, S.E., Robertson, M., Inman-Bamber, N.G., 2005. Decline in the growth of a sugarcane crop with age under high input conditions. Field Crop. Res. 92, 305–320. http://dx.doi.org/10.1016/j.fcr.2005.01.025.
Popova, Z., Kercheva, M., 2005. CERES model application for increasing preparedness to climate variability in agricultural planning–calibration and validation test. Phys. Chem. Earth 30, 125–133 (Parts A/B/C).
Rabbinge, R., 1993. The Ecological Background of Food Production, In: Ciba Foundation Symposium 177-Crop Protection and Sustainable Agriculture. John Wiley & Sons, Ltd., pp. 2–29.
Ray, D.K., Ramankutty, N., Mueller, N.D., West, P.C., Foley, J.a., 2012. Recent patterns of crop yield growth and stagnation. Nat. Commun. 3, 1–7.
Sacks, W.J., Kucharik, C.J., 2011. Crop management and phenology trends in the U.S. Corn Belt Impacts on yields, evapotranspiration and energy balance. Agric. For. Meteorol. 151, 882–894.
Soler, C.M.T., Sentelhas, P.C., Hoogenboom, G., 2007. Application of the CSM-CERES-Maize model for planting date evaluation and yield forecasting for maize grown off-season in a subtropical environment. Eur. J. Agron. 27, 165–177.
Stuart, A.M., Pame, A.R.P., Silva, J.V., Dikitanan, R.C., Rutsaert, P., Malabayabas, A.J.B., Lampayan, R.M., Radanielson, A.M., Singleton, G.R., 2016. Yield gaps in rice-based farming systems: insights from local studies and prospects for future analysis. Field Crop. Res. 194, 43–56.
Sun, H., Zhang, X., Wang, E., Chen, S., Shao, L., Qin, W., 2016. Assessing the contribution of weather and management to the annual yield variation of summer maize using APSIM in the North China Plain. Field Crop. Res. 194, 94–102.
Van Heerden, P.D.R., Donaldson, R.A., Watt, D.A., Singels, A., 2010. Biomass accumulation in sugarcane: unravelling the factors underpinning reduced growth phenomena. J. Exp. Bot. 61, 2877–2887. http://dx.doi.org/10.1093/jxb/erq144.
Van Ittersum, M.K., Cassman, K.G., Grassini, P., Wolf, J., Tittonell, P., Hochman, Z., 2013. Yield gap analysis with local to global relevance-A review. Field Crop. Res. 143, 4–17.
Van den Berg, M., Singels, A., 2013. Modelling and monitoring for strategic yield gap diagnosis in the South African sugar belt. Field Crop. Res. 143, 143–150.
Wang, F., Qin, F., Wu, D., Lou, F., Cen, T., Ge, C., Shi, N., 2015. Comparative study on the calculation method of soil organic matter and organic carbon. J. Agric. 5, 54–58.
Wegener, M.K., Jones, C.A., Russell, J.S., 1988. Simulating cane growth under Australian conditions. Proc. Aust. Soc. Sugarcane Technol. 99–106.
Wegener, M., Ou, Y., Yang, D., Chen, L., Yu, P., 1999. Mechanisation of sugarcane production in China: experience with sugarcane machinery on guang qian state farm. Aust. Agric. Resour. Econ. Soc. 19–22.
Welch, J.R., Vincent, J.R., Auffhammer, M., Moya, P.F., Dobermann, A., Dawe, D., 2010. Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. Proc. Natl. Acad. Sci. 107, 14562–14567.
Wiedenfeld, R.P., 1995. Effects of irrigation and N fertilizer application on sugarcane yield and quality. Field Crop. Res. 43, 101–108.
Willmott, C.J., 1981. On the validation of models. Phys. Geogr. 2, 184–194.
Willmott, C., 1982. Some comments on the evaluation of model performance. Bull. Am. Meteorol. Soc. 63, 1309–1313.
Xian, F., Guo, J., Zhang, Y., 2014. Progress of sugarcane at home and abroad nutrient management. Sugar Crop. China 71–73.
Xiao, D., Tao, F., 2014. Contributions of cultivars, management and climate change to winter wheat yield in the North China Plain in the past three decades. Eur. J. Agron. 52, 112–122.
Yinggang, O., Wegener, M., Dantong, Y., Qingting, L., Dingke, Z., Meimei, W., Haochun, L., 2013. Mechanization technology: the key to sugarcane production in China. Int. J. Agric. Biol. Eng. 6, 1–27.
Zhijuan, L., 2013. Theyield Gaps and Constraint Factors of Spring Maize in Northeast China. China Agricultural University.
Zhixiong, L., 2012. Sugar security situation and international comparison under opening conditions. Issues Agric. Econ. 77–84.