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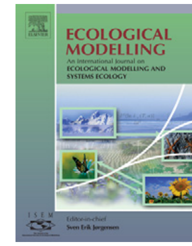

A crop model cross calibration for use in regional climate impacts studies

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ABSTRACT

Crop simulation models are widely used to assess the impacts of and adaptation to climate change in relation to agricultural production. However, a substantial mismatch often exists between the spatial and temporal scale of available data and the requirements of crop simulation models. Conventional model calibration methods which concentrate on a model's performance at plot scale cannot be used for large scale regional simulation (especially for climate change impacts assessments), given the limited observed data and the iterative calibration needed. One primary purpose of regional simulation is to predict the spatial yield variation and temporal yield fluctuation. This purpose could be fulfilled through model input calibration in which the objective of the calibration focuses on spatial or temporal agreement between simulated and observed values. This study examines the performance of CERES-Rice at the regional scale across China using a cross calibration process based on limited experiment data, agroecological zones (AEZ) and 50 km × 50 km grid scale geographical database. Model performance is evaluated using rice yields from experimental sites at the plot scale, and/or observed yield data at the county scale. Results suggest: the CERES-Rice model was able to simulate the site-specific rice production with good performance in most of China, with a root mean square error (RMSE) = 991 kg ha^{-1} and a relative RMSE = 14.9% for yield across China. The cross calibration process, in which AEZ-scale parameter values were derived, gave a relative bigger bias to yield estimation, with a RMSE = 1485 kg ha^{-1} and a relative RMSE = 22.5%, but achieved a reasonable agreement with observed maturity day and yield at spatial scale. The bias rose further if this cross calibrated model was used to simulate the real farmer rice yields at a regional scale, with a RMSE = 2191 kg ha^{-1} and relative RMSE = 34% across China. The pattern of yield variation was captured spatially by the model in most of the rice planting areas, but not temporally. The sources of uncertainties were analyzed for both plot scale and regional scale simulation. This calibration process could be incorporated into climate change integrated assessment and adaptation assessment, especially for those developing counties with limited observed data.

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1. Introduction

Physically based, plot-specific crop models, whose input parameters have a physical interpretation and explicit representation of environmental and varietal variability, have been widely used to explore the impacts of climate change on potential food production and adaptation options (Rosenzweig and Hillel, 1998; Hoogenboom, 2000), at both global (Parry et al., 1999) and national or regional scales (Alexandrov et al., 2002; Hoogenboom, 2000; Reilly, 2003). However, there are many sources of uncertainty in such studies, including the future emission rates of greenhouse gases (Gupta et al., 2003), and differences in the climate scenarios produced by different global climate models (Tubiello et al., 2002; Tsvetsinskaya et al., 2003; Easterling et al., 2001). Uncertainties also exist in relation to the application of plot-specific crop models to the estimation of crop production in large areas (Hansen and Jones, 2000; Challinor et al., 2004). This arises from the scale mismatches between plot-specific crop models, global (or regional) climate model outputs and regional agricultural production. Most crop models are designed to represent the plot scale and this makes it difficult to predict the impact of climate change at a regional level, unless some major assumptions are made to upscale results (Hoogenboom, 2000; Challinor et al., 2005). The conventional approach in impacts studies has been either to run a model for several sites, and then upscale the results to the regional scale (Iglesias et al., 2000), or to model regional yields using region-specific representative soil(s) types, crop varieties, and management practices (Moen et al., 1994; Haskett et al., 1995).

The underlying assumption in crop modeling applications is that the model can accurately simulate the processes occurring within the agricultural system (Thorp et al., 2005). Model calibration is needed to optimize the model input parameters, either for plots across different conditions (e.g. Cheyglinted et al., 2001; Mall and Aggarwal, 2002), or for regions which have a relatively homogeneous condition. However, a lack of sufficient data to fully characterize spatial variability and scale problems of integration of field measurements and model parameters hinders the model calibration and validation for regional simulation, especially for climate change impacts.

All crop models should be calibrated and validated for the environment of interest if results are to be credible (Timsina and Humphreys, 2006). Model calibration involves minimizing the error between model outputs and observed data and the determination of model parameters for an intended purpose (Jones et al., 2003). Model validation assesses the ability of a calibrated model to simulate the characteristics of an independent dataset (e.g. Irmak et al., 2005; Carbone et al., 2003). For regional impact assessments of climate change, the large geographical area and limited observed data, means that calibration is usually confined to using results from yield trials from agricultural experiment stations (Mavromatis et al., 2001; Mavromatis et al., 2002) (e.g. Trnka et al., 2004; Alexandrov et al., 2002), or the most commonly cultivated crop varieties (e.g. Saseendran et al., 2000; Jin, 2003). Selection of calibration sites may be rather arbitrary, driven by data availability rather than a true representation of regional practices or spatial heterogeneity. There is a need for a more practical and robust calibration process suitable for regional simulation, especially for climate change impacts assessment. It should concentrate more on predicting the pattern or trend of agricultural production at both spatial and temporal scales, by using currently available limited geographical data and models, rather than on estimating precise farm production.

The agro-ecological zones (AEZ) system, which defines land units in terms of climate, soil and terrain characteristics relevant to specific crop production (Fischer and Van Velthuizen, 1999) provides useful information on the geographical distribution of crop genotypes and management practices. Combining results form yield trials and AEZ could provide a possible method of model calibration and validation for large scale climate impact studies. This approach not only simplifies the time-consuming calibration and validation process, but also captures the spatial heterogeneity of variety maturation group, crop management and climate.

The objectives of this paper are as follows:

(a) To present a crop model cross calibration approach for use in regional climate impacts assessment based on limited observed experimental yield data and representation of spatial variability using agro-ecological zones.
(b) To develop a regional up-scaling methodology to go from the plot-specific crop modeling to an aggregated grid scale database (here we use a 50 km × 50 km resolution).
(c) To test the cross calibration approach and the up-scaling methodology by comparing (across space and time) CERES-Rice simulated yields with observed yields.
(d) To analyze the difference between simulated potential yields and observed agricultural production figures at plot and national scales to understand better the relationship between simulated potential yields and actual production.

2. Material and methods

2.1. Crop model

The CERES-Rice crop model (Singh et al., 1993) was used, which is embedded in DSSAT35 (Tsuji et al., 1994; Hoogenboon et al., 1999). CERES-Rice is a physiologically based, management-oriented model that utilizes carbon, nitrogen, water and energy balance principles to simulate the processes that occur during the growth and development of rice plants within an agricultural system. CERES-Rice has been widely used to simulate the collective effects of plant genetics, management practices, weather, and soil conditions on the growth, development, and yield of rice plants (e.g. Mahamood et al., 2003; Singh and Padilla, 1995; Jin et al., 1995; Mall and Aggarwal, 2002). The model calculates the growth and development of rice plants within a homogeneous area on a daily time step, and the final crop yield is computed on the date of harvest. Inputs required for model execution include management practices (plant genetics, plant population, row spacing, planting and harvest dates, and fertilizer application amounts and dates), environmental factors (soil type, drained upper and lower limits, saturated hydraulic conductivity, etc.) and weather conditions (daily minimum and maximum temperature, solar radiation, and precipitation).

A number of adjustable genetic coefficients are used in CERES-Rice to characterize the growth and development of crop varieties which differ in maturity: the thermal units required to complete the juvenile stage (parameter P1), critical photoperiods (P20), the extent to which phasic development leading to panicle initiation is delayed for each hour increase in photoperiod above the critical photoperiod (P2R), and the thermal units for the grain filling period (P5). Others genetic coefficients specify growth and yield characteristics—the number of spikelets per unit dry matter of the main culm (G1), the single grain weight under ideal growing conditions (G2), the relative tillering potential (G3), and the tolerance coefficient for the thermal environment (G4).

2.2. Background to the study area and rice production

Rice is the main staple food in China. National production was 181 million metric tonnes in 2004 (FAOSTAT database) which accounted for 30% of global rice production (FAO, 2004). The 29 million ha of rice cultivation in China (FAOSTAT database) is distributed across temperate, subtropical, and tropical belts, with the greatest production in the subtropical belt. Over 95% of the total harvested rice area is irrigated (Maclean et al., 2002), mostly in the southeast, south and northeast of China. Small, scattered areas of production occur in north, northeast and northwest China.

Based on climate, latitude, and topography, rice production has been divided into six major AEZs (Table 1 and Fig. 1) by Zhu and Min (2001). These six zones have been further subdivided into a total of 16 sub-AEZs, based on physical conditions, topography, soil and geological formation, rainfall patterns, cropping systems, and the development of irrigation. Over 95% of the rice area is located in AEZs 1, 2 and 3. The smallest area of rice cultivation is in zone 6, which only accounts for 0.5% of the total area (Zhu and Min, 2001). Most of the double cropped rice is concentrated in sub-AEZs 11, 13, 21, 23, and 31, with small areas scattered in sub-AEZs 12 and 32.

2.3. Data preparation

2.3.1. Experimental data and yields data from agricultural census

The data on rice phenology, yields, yield components (such as biomass, byproduct dry weight, pod per panicle, grain unit dry weight, etc.), and management practices from 1998 to 2000 are available from local agricultural meteorological experimental stations maintained by the Chinese Meteorological Administration (Tao et al., 2006). In total 522 yield experiments were selected that: (1) represent the major paddy rice planting areas in China where almost all of China's paddy rice production (>95% of area) is concentrated (Fig. 1); (2) had no records of significant damage due to pest, weed or extreme climate events. There are 195 yield experiments on single season rice from 65 stations and 327 experiments on double season rice from 54 stations. Conditions at the stations range from the moderately warm, humid, and single rice season regions of northeast China to the tropical monsoon, more humid, and double rice season regions of Hai Nan province, South China. Crop management practices in the experimental stations were generally better than local traditional practice. Management practices at most stations did not change much during the study period, except for change in varieties. Irrigation was used several times every year to keep the rice field flooded until the end of grain filling period. Fertilizer was applied, usually two or three times every season, and pesticides were also frequently applied to control pests and diseases.

In additional to the experimental station data, historical annual county census rice yield data for the whole of China were provided by the Institute of Agricultural Resources and Regional Planning (IARRP) and the Chinese Academy of Agricultural Sciences (CAAS) for the period 1981–2000. The yields were de-trended to the year 2000 technology level using a linear trend analysis technique (Hollinger et al., 2001). The county yields were then aggregated to a 50 km × 50 km grid level yields using an area-weighting approach (Jagtap and Jones, 2002).

2.3.2. Weather data

Daily climate variables (maximum and minimum temperature, precipitation, and hours of sunshine) from 680 sites were provided by the Chinese Meteorological Data Center for a time series of 20 years (1981–2000). Daily solar radiation for each time series was calculated from a linear relationship with n/N (actual daily hours of sunshine/maximum daily hours of sunshine), according to Pohlert (2004). Each experimental station and 50 km × 50 km grid was assigned the closest meteorological site.

2.3.3. Soil data

Crop model inputs related to soil include albedo and runoff Curve Number. For each soil layer, inputs include depth; texture; water-holding capacity at drained lower and upper limits and at saturation; bulk density; pH; and organic carbon. A soil characteristics database (containing soil layer; depth; texture; bulk density; pH; and organic carbon) corresponding to the 1:1,000,000 scale soil map of China was provided by the Soil and Fertilization Institute (SFI) and CAAS (Chinese National Soil Survey Office, 1998). Soil water characteristics (including water-holding capacity at drained lower and upper limits, and at saturation) were calculated from soil texture, organic carbon and bulk density according to Rawls et al. (1982). A spatial data processing method described in Knox et al. (2000) was used to transfer soil properties of agricultural soils from mapping units into the 50 km × 50 km grid cell unit, and to aggregate the soil properties into median values for topsoil (0–30 cm) and subsoil (30–100 cm) from the original values distributed across each profile layer, so that averaged soil properties were generated for each grid.

2.3.4. Management data

The management data required by CERES-Rice are sowing date, sowing density, row width, transplanting date, fertilizer application times, date and amount, irrigation application times, date and amount. Values to represent management practices in the model were selected from all relevant sites in the experimental site data set.

Table 1 – Description of the AEZs in China and their main cropping systems, including rice cropping area (yields and areas are retrieved from Zhu and Min, 2001)

AEZ	Sub-AEZ	Main cropping system	Rice areas (10^3 ha)	Average yields (kg ha^{-1})	Sowing date
1. South China (double season rice)	11	Double rice + WC	4930.7	4200	First: February 24–March 18; second: June 25–July 18
	12	Single rice + WC	491.3	3520	March 25–April 10
	13	Double rice + WC	602.7	2775	First: January 1–30; second: June 1–30
2. Yangtze river zone (double season and single season rice)	21	Double rice + WC	9488.7	4770	First: April 1–May 23; second: June 15–July 23
	22	Single rice + WC	3187.3	5220	March 21–April 21
	23	Double rice + WC	10478.0	4230	First: February 12–April 21; second: June 9–July 4
3. Southwest plateau (single and double season rice)	31	Double rice + WC	1545.3	4260	First: April 1–17; second: June 5–July 1
	32	Single rice + WC	1130.7	4455	March 12–April 20
	33	Single rice + WC	2.0	3375	April 10–28
4. North China (single season rice)	41	Single rice + WC	260.7	4800	April 26–May 10
	42		858.7	4515	April 1–24
5. Northeast China (early maturing single season rice)	51	Single rice	459.3	4155	April 1–24
	52		401.3	6090	April 10–May 10
6. Northwest China (single season rice)	61	Single rice	28.0	3270	April 10–May 10
	62		66.0	2965	April 10–May 10
	63		93.3	5760	April 10–May 10

WC: winter crop, which usually are winter wheat, barley, oil seed rape, etc.

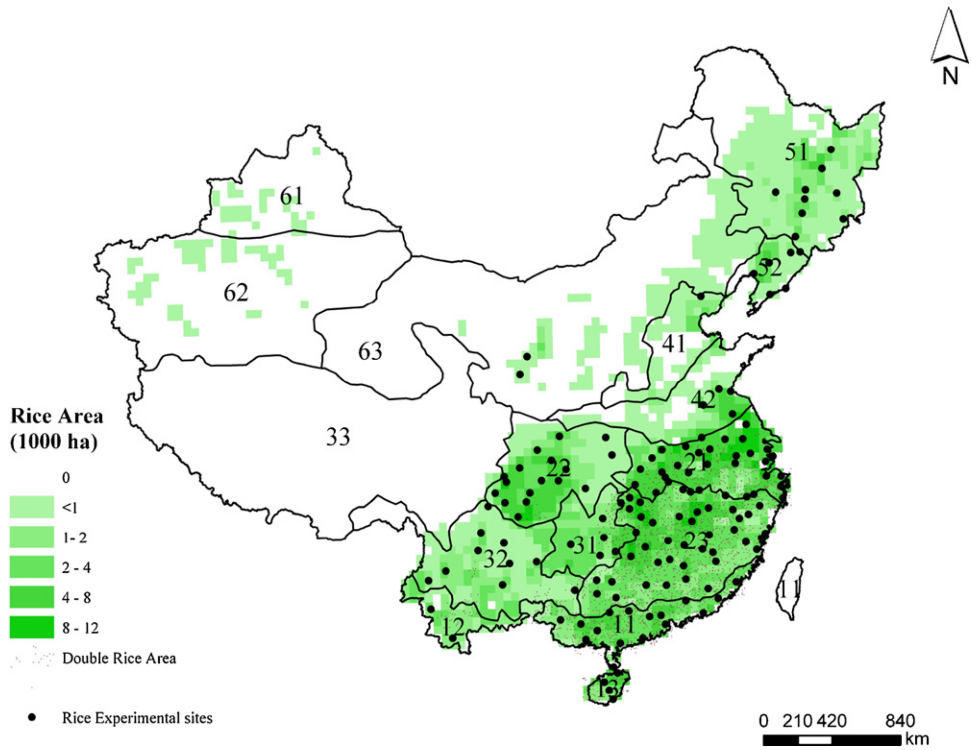

Fig. 1 – The distribution of rice growing areas (1990) within the agro-ecological zones of China (the shading indicates the areas with double rice planting (1990), and black dots are the rice experimental sites).

2.4. *Cross calibration and regional simulation*

2.4.1. *Cross calibration and validation*

The parameters that define a rice variety in CERES model only refer to dates of development and accumulation of dry matter; many other variety characteristics are not defined by these coefficients (such as drought resistance, pest and disease resistance, etc.). Therefore, a particular set of coefficients may be representative of a group of varieties of similar characteristics in a particular geographical area. For regional simulation, we assumed one maturity group variety was sown and a prevalent management practice was implemented across all regions in each sub-AEZ and season (first and second season of double rice and single season rice). In order to determine best representative varieties and their management practices for those sub-AEZs and seasons, a cross calibration approach of Thorp et al. (2005) was employed. With the 3 years of available observed site-specific experimental yield data, cross calibration requires that the model be calibrated three times in each sub-AEZ and season by alternatively leaving out 2 years of observed data. The model is then evaluated against the observed data for the 2 years left out of the calibration. The parameters values which result in minimum bias between observed and simulated values of all sites and validation years were selected for that sub-AEZ and season. To limit the amount of computation, and based on a model sensitivity analysis, only four variety parameters (P1, P5, G1, G2) and three management practices (sowing date, transplanting date, sowing density) were cross calibrated. Water availability, nutrition (which was set to automatic application in the simulations), pests, and disease occurrence were assumed to exert no stress on rice growth as the experimental stations usually support better management practices than normal farms.

The proposed parameter adjustment has two steps, as follows:

Step 1. Initialization of sub-AEZ parameters through site-specific calibration and validation
GENCALC (software to estimates the variety coefficients via iterations of deterministic processes, Pabico et al., 1999) was used to calibrate the variety parameters for all sites and seasons in each sub-AEZ, irrespective of variety maturity type (Hunt et al., 1993). These calibrations used the gridded soil database, observed field management practices at each site, and weather data from 1998. Validation at each site was done using data for 1999 and 2000. The optimum site-specific variety coefficients (P1, P5, G1, G2, P2R, P20, G3, G4) and management parameters (sowing date, transplanting date, sowing density, row spacing, planting depth) were then averaged across all sites within a given sub-AEZ and season. Having specified the parameters (P2R, P20, G3, G4, row spacing, planting depth) which would not be adjusted in step 2 for each sub-AEZ and season, a range of possible values was taken from Hunt et al. (1993) for the parameters which would be cross calibrated in step 2.

Step 2. Cross calibration and validation of sub-AEZ parameter values

With fixed variety coefficients and management parameters derived from step 1 for each sub-AEZ and season, we analyzed the sensitivity of the crop biological responses to changes in the coefficients that relate to phenology and yields components. The simulated dates of anthesis and maturity dates are sensitive to P1 and P5, respectively, and simulated grain weight and grain number m^{-2} are sensitive to G1 and G2, respectively. For each sub-AEZ and season, the cross calibration was used to calibrated P1 and P5 first by iteratively running the model using incremental changes in coefficients. The calibration objective was to minimize the RMSE of the observed and simulated phenological dates across all sites in the calibration years. After calibration of the phenology coefficients we adjusted the yield component coefficients G1 G2 to represent as accurately as possible the grain weight, and the grain number m^{-2}. Finally, after determination of the variety efficiencies, we calibrated the sub-AEZ scale management practices (sowing date, transplanting date, sowing density) by using observed yields, again to minimize the RMSE of simulated and observed yields.

2.4.2. *Validation of regional simulation for annual yields*

Using the cross calibrated variety and management parameters, grid scale annual rice yields were simulated from 1981 to 2000, and compared with the observed de-trended average annual rice yields. The final calibrated variety parameter values and appropriate management practices for each sub-AEZ and season, based on the cross calibration, are given in Table 3. Water was assumed to exert no stress on rice growth, with 50 mm water applied as irrigation when the soil water content was less than 0.8 of field capacity. Nitrogen was applied as ammonium nitrate before transplanting (100 kg ha^{-1}), with the remainder (200 kg ha^{-1}) applied after 60 days after transplanting, based upon the average fertilizer application at the experimental stations.

2.5. *Analysis*

For the site scale simulations, the bias of simulated crop phenology and yields were compared against observed plot scale data using means and standard deviations (S.D.), linear regression parameters intercept (α), slope (β), and coefficient of determination (r^2), Pearson correlation coefficient (r), root mean square error (RMSE), relative RMSE and *D*-index. For the regional validation, mean, S.D., RMSE, and the coefficient of residual mass (CRM, a negative value indicates that the majority of simulated values are greater than the observed values, and a positive value *vice versa*, Smith et al., 1996; Loague and Green, 1991) were used to evaluate the errors in the cross calibration.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \quad (1)$$

$$\text{relative RMSE} = \frac{1}{\bar{O}}\sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \quad (2)$$

$$D\text{-index} = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}[|P'_i| + |O'_i|]^2}\right] \quad (3)$$

$$\mathrm{CRM} = \frac{\sum_{i=1}^{n}O_i - \sum_{i}^{n}P_i}{\sum_{i=1}^{n}O_i} \quad (4)$$

where $P'_i = P_i - \bar{O}$ and $O'_i = O_i - \bar{O}$, P_i is the simulated value of the *i*th year, O_i is the *i*th year observed value. These statistics have been widely used for model evaluation, see for example, Willmott (1982) or Kobayashi and Salam (2000) for more detailed explanation.

3. Results

3.1. *Cross calibration and determination of parameters for sub-AEZ and season*

Table 2 shows the RMSE in annual yield from the cross calibration and validation for each sub-AEZ and season combination. Parameters values which gave the lowest total RMSE (RMSE of calibration + RMSE of validation) were selected for the next simulation.

3.2. *Performance of cross calibration simulation compared to experimental values*

Simulation results using the cross calibrated values listed in Table 3, and assuming no stress to rice growth from water and nutrition, were compared against the experimentally measured values for 1998–2000 (Table 4). Observed maturity dates ranged from 89 to 184 days, and grain yields from 1861 to 13372 kg ha^{-1}, the corresponding simulated values were from 94 to 258 days, and from 4243 to 10803 kg ha^{-1}, respectively. The simulated mean number of days to reach physiological maturity did not differ significantly from the observed values in the majority of AEZs except AEZ 1 and 2, with a RMSE = 13 days (10.6% of the observed mean), *D*-index = 0.62, and RMSE = 25 days (19.8% of the observed mean), *D*-index = 0.69, respectively. This could be largely attributed to the overestimation of first season rice (in which photoperiod sensitive varieties are usually planted) in these two AEZs, where the homogeneous input parameters could not capture the large variation in photoperiod sensitive varieties, especially for early planting dates. For varieties that are insensitive to photoperiod which are usually planted as second season rice, or later planted single rice, the model achieved good agreement with observed values (e.g. RSME = 11 days (8.5% of the observed mean) and *D*-index = 0.96 for second season rice). The *D*-index of simulated maturity date against observed values was high overall (*D* = 0.83) and in the majority of AEZs, which suggested that the model captured the pattern of phenological variation spatially and temporally.

The model predicted reasonable rice yields across all sites and seasons, with RMSE% = 22.4% and *D* = 0.77 overall. The

Table 2 – Average RMSE of annual yields for model calibration and validation by sub-AEZs and seasons

AEZs	Sub-AEZs	Season	Calibrated year: 1998, validation years: 1999, 2000 RMSE (kg ha^{-1})		Calibrated year: 1999 validation years: 1998, 2000 RMSE (kg ha^{-1})		Calibrated year: 2000 validation years: 1998, 1999 RMSE (kg ha^{-1})	
			Calibration	Validation	Calibration	Validation	Calibration	Validation
1	11	E	923	1047	1061	988	998[a]	998
		L	926[a]	1174	950	1173	1298	994
	12	S	190	507	320	513	79[a]	218
	13	E	1062	1037	842[a]	999	1120	1179
		L	761[a]	1374	600	1470	1670	991
2	21	E	2257	2319	2371	2250	2202[a]	2327
		L	1166	851	792	1250	659[a]	1045
	22	S	1769	2001	2196	1717	1716[a]	2008
	23	E	1744[a]	1382	1533	1800	1298	1635
		L	1228	1892	1890[a]	1468	1965	1586
3	31	E	927	1319	988[a]	945	1163	1144
	32	L	82	1023	552[a]	717	1795	1356
		S	1076[a]	1332	1509	1561	1179	1670
4	41	S	384	541	240	1030	175[a]	563
	42	S	235	1356	792[a]	1054	1239	1216
5	51	S	2784	1846	1255[a]	2356	1972	2772
	52	S	1477[a]	832	911	1232	815	1436
6	61	S	70	809	142[a]	620	372	588

Note: E is early season rice (double season rice); L is later season rice (double season rice); S is single season rice.

[a] Means these calibrated parameters values were selected for the regional simulation.

Table 3 – Cross calibrated representative variety parameter values and management practices for sub-AEZs and growing seasons

AEZs	Sub-AEZs	Season	P1 (PTD)	P2R (PTD)	P5 (PTD)	P20 (h)	G1 (no./g)	G2 (g)	G3	G4	SOW (dap)	TPLT (dap)	DENS (no./m^2)
1	11	E	425	113	330	10	55	0.022	0.99	1.04	55	26	70
		L	361	161	376	10	53	0.021	0.97	0.98	204	36	50
	12	S	267	183	307	10	33	0.029	1	1	91	40	60
	13	E	504	127	327	10	43	0.026	1	1	25	24	30
		L	238	190	518	10	43	0.024	1	1	177	26	30
2	21	E	542	110	470	11	48	0.026	0.97	0.98	93	24	30
		L	856	119	348	13	47	0.028	1	0.99	183	40	30
	22	S	336	132	331	10	48	0.028	1	1	83	24	30
	23	E	426	63	384	12	51	0.026	1	1.06	68	26	60
		L	413	109	461	12	63	0.027	1	1	174	20	40
3	31	E	503	108	505	11	47	0.028	1	1.02	121	26	30
		L	505	80	424	12	134	0.029	1	1	184	26	30
	32	S	585	78	250	13	53	0.027	1	1	81	40	120
4	41	S	805	116	458	12	37	0.026	1	1	81	40	120
	42	S	643	128	509	12	47	0.027	1	1.08	93	40	110
5	51	S	368	50	298	15	127	0.027	0.98	1	117	30	40
	52	S	565	60	371	13	49	0.026	1	1	111	24	40
6	61	S	545	50	614	14.4	63.5	0.023	1	1	88	24	80

Notes: PTD, photothermal days; SOW, sowing date; dap, day after planting; TPLT, transplant date; DENS, planting density.

Table 4 – Error statistics for AEZs irrespective of variety maturity group

AEZs	1	2	3	4	5	6	Total country	
							Cross calibration	Site calibration
n	111	309	30	18	48	6	522	522
Maturity day (d)								
X_{obs} (S.D.)	123(12)	126(18)	148(23)	155(14)	157(10)	162(8)	132(20)	132(20)
X_{sim} (S.D.)	125(10)*	131(21)*	148(30)	158(15)	158(26)	178(11)	135(23)	135(21)*
α	89.203	70.438	38.417	25.847	68.851	−26.888	63.954	24.40
β	0.297	0.483	0.745	0.854	0.383	1.260	0.498	0.797
r	0.124	0.172	0.321	0.613	0.099	0.875	0.323	0.722
r^2	0.352**	0.414**	0.566**	0.783**	0.313**	0.936*	0.569**	0.850**
RMSE (RMSE%)	13(10.6%)	25(19.8%)	24(16.2%)	10(6.5%)	31(19.0%)	16(9.7%)	22(16.7%)	12(8.8%)
D	0.62	0.69	0.84	0.87	0.34	0.57	0.83	0.95
Yield (kg ha^{-1})								
X_{obs} (S.D.)	5812(1123)	6519(1646)	7507(1278)	7218(1180)	8029(1471)	9537(417)	6628(1638)	6628(1638)
X_{sim} (S.D.)	6030(678)*	6748(1032)*	8066(1119)*	7948(977)*	7898(590)	8874(773)	6868(1182)*	6593(1760)
α	1210.9	2082.63	2776.214	1779.031	6583.867	15238.45	1789.109	1644.6
β	0.763	0.509	0.587	0.684	0.164	−0.667	0.706	0.757
r	0.212	0.102	0.272	0.315	0.167	0.129	0.251	0.689
r^2	0.461**	0.319**	0.522**	0.561**	0.408**	0.360	0.501**	0.830**
RMSE (RMSE%)	1028(17.7%)	1672(25.6%)	1270(16.9%)	1233(15.4%)	1333(16.6%)	1129(11.8%)	1485(22.4%)	991(15%)
D	0.65	0.62	0.86	0.69	0.51	0.22	0.77	0.92

* Simulation results significantly different to observed (two-paired t-test, α=0.05).
** Correlation is significant at the 0.01 level (two-tailed test); RMSE% denotes the relative RMSE against observed average values.

RMSE ranged from 1129 kg ha^{-1} in AEZ 6 to 1672 kg ha^{-1} in AEZ 2. The mean simulated yield across all stations and seasons was slightly higher (3.4%) than the mean observed yield, with this difference being significant in AEZ 1, 2, 3, and 4 (paired sample t-test, $\alpha = 0.05$). The cross calibrated model tended to under-predict high observed yields and over-predict low yields, giving a smoother yield distribution pattern compared to the observations, so that the S.D. was lower for simulated yields than observed yields for all AEZs and the country. Correlation between simulated and observed yields was significant in all AEZs except 6, and the D indexes ranged from 0.22 at AEZ 6 to 0.86 at AEZ 3, suggesting that the simulation performed well in predicting the spatial and temporal variation in some areas, while not in others.

The cross calibrated simulation increased the root mean square error from 991 kg ha^{-1} (17% of observed mean) in the traditional site calibration simulations to 1485 kg ha^{-1} (22.4% of observed mean). This increase in error could be attributed to the increased uncertainties in model parameters values, namely those for the representative varieties and their management practices. The biggest discrepancy occurred in AEZ 2 (RMSE = 1672 kg ha^{-1} (25.6%), D-index = 0.62), especially for first season rice in sub-AEZ 21 (RMSE = 2041 kg ha^{-1} (27.5%), D-index = 0.39), sub-AEZ 23 (RMSE = 1542 kg ha^{-1} (26.7%), D-index = 0.24), and single rice in sub-AEZ 22 (RMSE = 1881 kg ha^{-1} (25.5%), D-index = 0.24), which suggests that the calibration should be improved for the photoperiod-sensitive varieties in these areas.

3.3. *Regional simulation and comparison to the observed farm production (census yield)*

Annual rice yields from 1981 to 2000 were simulated across China, with rice yield for the double rice area calculated as following

$$Y = Y_e \times (1 - A_d) + \left(\frac{Y_e + Y_l}{2}\right) \times A_d \qquad (5)$$

where Y is the yield, Y_e, and Y_l are the yields of the first and second rice yield. A_d is the proportion of double rice area to total rice area. The proportion of double rice area in 1990 was from Frolking et al. (1999) and was used for all years due to a lack of data.

Table 5 shows the statistical comparison between simulated and census yields. The simulated mean yield of 1981–2000 was significantly higher (two-paired t-test, $\alpha = 0.05$) overall and for most of the sub-AEZs, except sub-AEZ 12, 21, 23 (where the simulated mean was lower than the census values) and 41 (where the simulated mean was not significantly different from the census values). The highest overestimation of mean yield occurred in sub-AEZ 33 (72% higher than the mean yield). The mean RMSE across all grids and years was 2191 kg ha^{-1} (34.4% of the mean observed yield), and the mean RMSE of the sub-AEZs ranged from 771 kg ha^{-1} (15%) at sub-AEZ 13 to 4226 kg ha^{-1} (74%) at sub-AEZ 33. The bias was lowest in 1983 (mean RMSE across all grids was 1879 kg ha^{-1}, relative RMSE = 27%), and highest in 1999 (RMSE = 3756 kg ha^{-1}, relative RMSE = 35%). The simulated mean S.D. was lower than the census S.D. overall and for all the sub-AEZs, with the lowest underestimate in S.D. in sub-AEZ 32 (6% underestimation), and highest underestimate in sub-AEZ 41 (76% underestimation). The simulated mean yields were significantly spatially correlated with census values in most of the sub-AEZs, except 11, 12, 31, 33, and 42, which suggests the simulation can capture the main patterns of spatial variation in yield for the majority of regions, particularly for the primary rice cultivation area (e.g. AEZ 2)

For the double rice areas (Fig. 2), the model performed very well for most regions to predict the spatial pattern of mean yield variation, giving either a slight underestimate or a result close to the census mean yields, with less than a 15% mean relative RMSE, and a mean 29% underestimate of S.D. However, for single rice areas, the model's performance varied across locations. The bias was larger in marginal rice planting areas (in the west of sub-AEZs 51, 63, and 32) which usually have relatively larger temporal yield fluctuations and spatial yield variation, while it was lower in some main cultivation areas with higher and more stable yields. However, for the single rice areas, the model produced a large overall overestimate of yield, a larger bias than with double rice areas (with mean RMSE = 2622 kg ha^{-1}, 42%), and a 49% underestimate of S.D. Simulation of annual yield variability by year was poor for most of the cells: only 271 of the 1883 total grids produced significant correlations between simulated and observed year-to-year yields (95% level of confidence, Fig. 3).

4. Discussion

4.1. *Performance of the cross calibrated model at the site scale and potential sources of bias*

The overall RMSE of the site calibrated model for all stations, seasons, and validated years was 991 kg ha^{-1} (15% relative to mean observed yield), D-index = 0.92 for grain yield, and RMSE = 12 (day) (8%) D-index = 0.91 for maturity date. These results suggest that CERES-Rice performed well under a wide range of environmental conditions in China when calibrated using direct field data, using criteria from other model evaluation studies (e.g. Saseendran et al., 1998; Matthews et al., 2000; Yao et al., 2007).

As in most regional crop simulations for climate impact studies, representative input parameters were used, which were determined by a cross calibration process, in this way the overall RMSE of yield increased to 1485 kg ha^{-1} (23% to mean observed yield) and D-index decreased to 0.75. The increased biases could be mainly interpreted by (1) the uncertainty caused by the constant variety parameters values and management practices which were different to the specific experiments; (2) overestimation of the yield because of the assumption that water and nutrition are not limiting; (3) overestimation of the yield due to the later simulated maturity date for photoperiod sensitive varieties (e.g. first season rice, and early planting single rice). The biases could be decreased if the calibration process was improved through more accurate identification of homogeneous regions and the availability of more experimental results. However, by using the cross calibrated input parameters, the model still showed a generally good agreement with the observed experimental yields. The

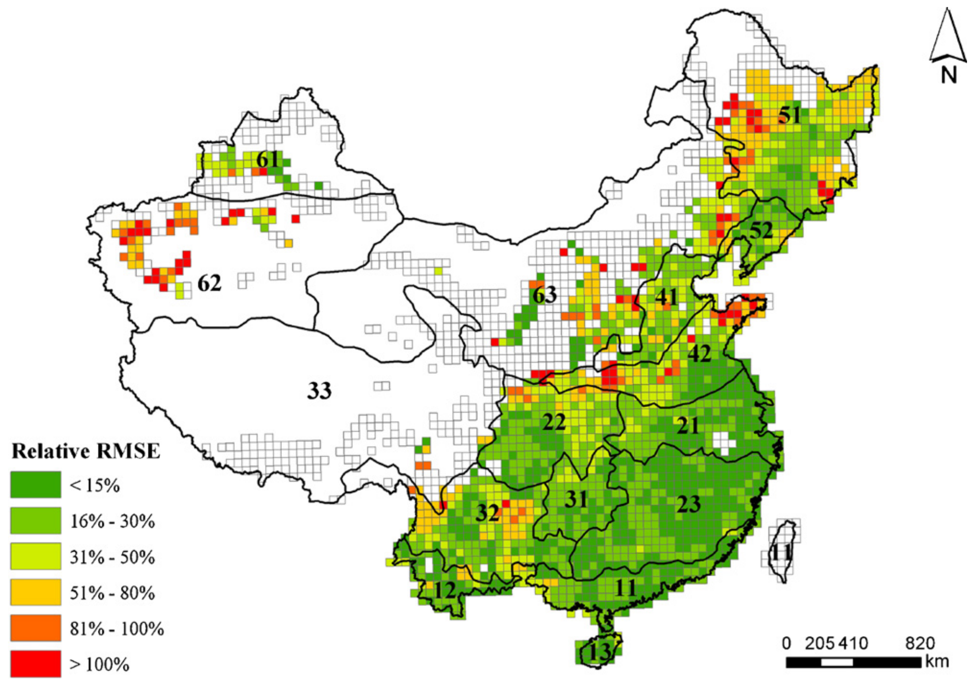

Fig. 2 – Relative RMSE of simulated yield to observed census yield (1981–2000) at 50 km × 50 km grid scale.

RMSE values are lower and the *D*-indexes are higher than those of other studies that also used representative parameter values (e.g. Jintrawat, 1995; Godwin et al., 1994), these could be largely ascribed to the specific objective of our cross calibration, namely calibrating the spatial agreement between observed and simulated values rather the model's performance at a specific plot.

However, the cross calibrated model's performance varied by region and season. For those regions in which the planted varieties differed from the assumed varieties on photoperiod sensitivity, the calibrated model did not perform very well, particularly in the overestimation of maturity date. The possible reasons are either that not all variety parameters and management practices were adequately calibrated in our cross

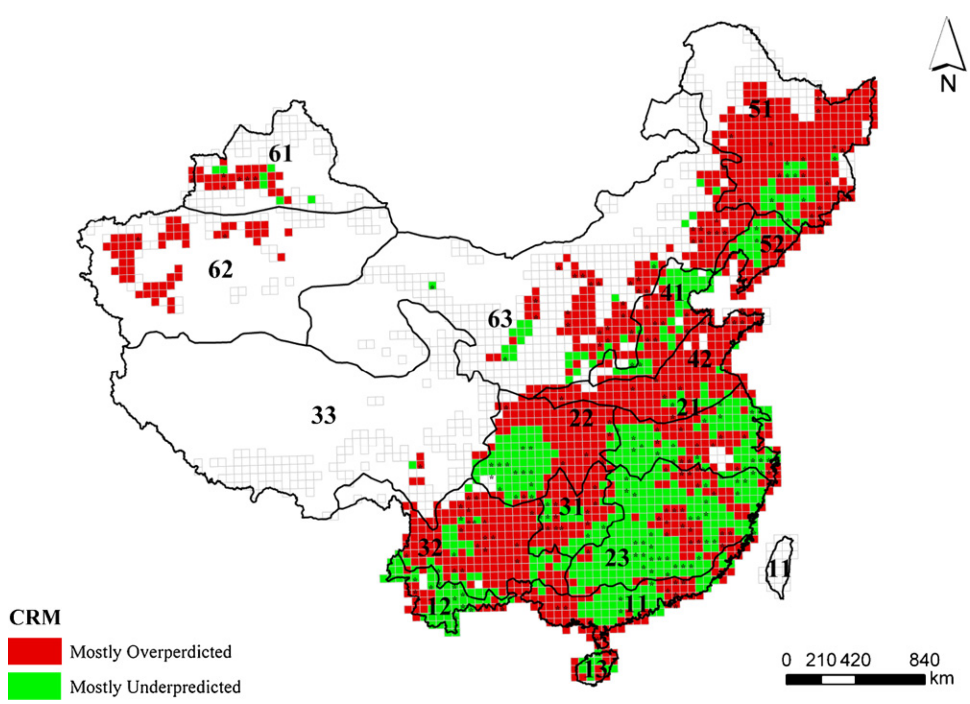

Fig. 3 – Coefficient of Residual Mass (CRM) of simulated yield to observed census yield (1981–2000) at 50 km × 50 km grid scale (* represents grid cells with significant correlation (5%) between observed and simulated yields (1981–2000)).

Table 5 – Error statistics for sub-AEZs for regional simulation (*X*, mean yields; S.D., standard deviation; RMSE, root mean square error; *r*, Pearson correlation coefficient; *D*-index, index of agreement; cen, census values; sim, simulated values)

AEZs	Sub-AEZs	Single	*N*	X_{cen} (kg/ha)	X_{sim} (kg/ha)	$S.D._{cen}$ (kg/ha)	$S.D._{sim}$ (kg/ha)	*r*	RMSE (kg/ha)	RMSE%	*D*-index
1	11	Double	2655	6202	6539	887	778	0.006	1229	20%	0.31
	12	Single	1342	5357	4700	1056	670	0.034	1395	26%	0.41
	13	Double	303	5144	5296	741	282	0.158**	771	15%	0.41
2	21	Double	2736	7765	7608	1499	868	0.226**	1519	20%	0.44
	22	Single	3125	7125	8023	1410	901	0.379**	2137	30%	0.41
	23	Double	5016	6453	6096	820	681	0.283**	973	15%	0.43
3	31	Double	1041	6657	7126	927	799	0.042	1285	19%	0.43
	32	Single	2722	6458	8216*	1297	1209	0.200**	2368	37%	0.47
	33	Single	58	5691	9764*	1070	733	0.246	4226	74%	0.46
4	41	Single	981	6151	6146	1770	430	0.076*	1852	30%	0.46
	42	Single	1988	6823	8566*	1729	746	0.010	2561	38%	0.43
5	51	Single	3168	6434	8402*	1860	774	0.165**	2900	45%	0.42
	52	Single	971	6701	7487	1655	633	0.212**	1820	27%	0.42
6	61	Single	323	8164	9667*	2102	729	0.202**	2795	34%	0.42
	62	Single	265	6409	8860*	2405	803	0.464**	3260	51%	0.43
	63	Single	1266	5734	9049*	1893	986	0.062*	3971	69%	0.42
Average for total country			27920	6582	8964*	1522	1430	0.40**	2191	34%	0.42

* Significant at 0.05 level.
** Significant at the 0.01 level.

calibration process, especially the parameters which are sensitive to photoperiod (in order to decrease the amount of calibrating computation, the photoperiod parameters of P2R and P20 which very influential on values of other parameters and simulation outputs were not calibrated), or the present AEZ classification of Zhu and Min (2001) is not appropriate or sufficient detail led to reflect the spatial variation, in terms of maturity type (e.g. variety photoperiod), management practices (early sown, later sown) or other issues under the present climate. The same overestimation of number of days to physiological maturity or anthesis has also been found by Tongyai (1994) and Boonjung (2000). Some studies, in which the variety parameters have been aggregated based on maturity group rather than on locations (e.g. Carbone et al., 2003), have achieved good agreement between observed and simulated maturity data. Therefore, calibration methods which aggregate the representative parameters for both AEZs and maturity groups would be employed in future to decrease the bias in these regions.

The current model failed to predict the large yield ranges in some areas, particularly for those with temperate climate and mountain regions, such as AEZ 5 and 3. This might result from the model's inability to correctly simulate sterility induced by extreme temperature damage (Godwin et al., 1994; Meyer et al., 1994), or because the same G4 (temperature tolerance coefficient) value was used for each sub-AEZ and season (we used a value of G4 for enduring the worst extreme temperature across all regions in each sub-AEZ and season).

4.2. The performance of the regional simulation and sources of the bias

The aim of the regional simulation was to closely match observed agricultural production, both spatially and temporally, using currently available geographical data. For climate impact assessments, the realistic estimation of baseline production reduces uncertainties and increases the robustness of assessments of future production.

Basically, the bias increased when the cross calibrated model was used to simulate the actual regional production rather than the experimental station yields. The mean relative RMSE across grids and years was 34% of the census yield. Possible sources of errors are:

(1) Representative coefficients for varieties and management parameters. In the cross calibration, variety coefficients calibrated from experimental stations are likely to differ from the real situation. Crop management practices in the experimental stations are generally better than the local practices (Tao et al., 2006). The assumption of no moisture stress does not represent the real situation in which water scarcity may occur in some years (Zhu and Min, 2001), and the static nutrition configuration, rather than a dynamic value across sub-AEZs and years, might sometimes over-estimate the annual yield. This is because fertilizer application has been the key determinant of crop yield growth in China, and has increased from 102 $kg\,ha^{-1}\,year^{-1}$ in 1980 to 612 $kg\,ha^{-1}\,year^{-1}$ in 2000 (China Statistics Bureau, 2001).
(2) Reliability of census data.
(3) Uncertainties related to the geographical data, e.g. average soil profile data within the gridded soil data (Knox et al., 2000) will not represent the variability in soil types found within an area.
(4) Others factors that the model does not account for, e.g. pests, diseases, extreme weather events, etc. (e.g. Chipanshi et al., 1999; Jagtap and Jones, 2002).

Spatially, this cross calibrated regional simulation has captured the spatial variation of mean yield for most of the regions, especially the primary rice cultivation area (sensitivity analysis suggested that the spatial performance of the regional simulation could be improved through employment of a more detailed AEZ system, more experimental sites, or aggregating inputs based on both the AEZs system and maturity groups). However, temporally, the regional simulation failed to reproduce the yields variability for most of grids, with only 14.4% of the simulated grids' series of yields producing significant correlations with observed yields. This is an important concern as it has been argued that accurate prediction of the range of interannual yield variability is more important than estimating mean yield values for climate impact studies because year-to-year variability has time greater potential economic impact (Moen et al., 1994). Possible causes of poor simulation of interannual variability include:

(1) Yield overestimation caused by the exclusion of other factors (e.g. irrigation water restrictions in dry years, pests, disease, extreme climate events, etc.).
(2) Changes in the proportion of double season rice area to total rice area with time, as the area of double season rice, as well as the rice cultivation area, changes every year in response to agricultural policy (e.g. water saving policy), markets (e.g. prices) as well as climate. Agricultural surveys could capture the fluctuations in cultivation area precisely, but not the distribution of crop rotation systems (Frolking et al., 1999). With data being used from 1990, this factor may have had an important impact on the error in annual mean rice yield in some years (Dawe et al., 2004), or in some regions, especially for those regions which are close to urban areas, and those years with major changes in agricultural or economical development policy.
(3) Homogeneity of input parameters smoothes the yield variation and decreases the S.D. (clear from the model calibration stage).
(4) Management assumptions do not represent reality. When considering the rice production by individual farmers, their management varies from year to year depending on the market, weather and cultivation culture, etc. It is not possible to capture all of this unknown farm-level variability in the model input parameters, as is found in most climate impacts studies (e.g. Saseendran et al., 2000; Kapetanake and Rosenzweig, 1997; Iglesias and Minguez, 1997; Alexandrov et al., 2002, etc.).

4.3. Application of this cross calibration and use of this regional simulation for climate impacts assessment

Very detailed calibration and validation of crop models on selected stations has been used before for impacts assessment studies (e.g. Yao et al., 2007; Tao et al., 2007, in the case of China). As with the site-specific calibration and validation in our study, they argued that the validated CERES-Rice model was able to estimate the rice phenology and yield adequately, with a bias of phenology of less than 10%, and yield of less than 15%. However, the calibration and validation at a few selected stations hinders the up-scaling required to use the crop model for regional simulations. Firstly, the plot scale calibration of the crop model in a few representative sites does not capture the spatial heterogeneity of climate, soil, management practices, and increases the simulation bias if results are arbitrarily up-scaled from site to region; Secondly, it is not easy for site-specific validation to provide a quantitative estimation of uncertainties before regional simulation, which are often desperately required by policy makers. For some developing counties with large territories, like China, their large spatial span and the scarcity of observed experimental, geographical (e.g. soil, weather data) and statistic data usually limits validation and simulation to some selected stations (e.g. Yao et al., 2007). Such site-specific simulations cannot supply the information on the overall impacts of climate change, or macro scale adaptation measures required for agricultural policy formulation and decision making, such as adjusting of planting structure (i.e. the proportion of different crops), construction of commodity grain base, etc.

Our study used available experimental datasets and agrometeorological information to provide a very detailed input calibration for a crop model to be used in regional climate change impacts simulation. The purpose of the cross calibration is to increase the spatial agreement of observed and simulated values, by using currently available data. By using this cross calibration process, the regional simulation can not only reflect the impacts of climate variability, but also the present patterns of rice planting and management, etc. Although it increased the bias compared to the site-specific validation, it provided important benefits on some issues: (1) to capture the heterogeneity of rice planting in China, and obtain the responses of rice production to climate change in different regions; (2) to up-scale the model for regional usage based on presently available data; (3) to provide a possibility of combining the results of crop simulation with that of other regional models, e.g. hydrological models, land use models, etc.; and (4) to calculate the uncertainties quantitatively before regional simulation. Furthermore, future scenarios, including climate change scenarios (temperature, changed precipitation patterns, CO_2), technological development scenarios (new varieties, enhanced fertilization application and high efficiency irrigation equipment), and socio-economic scenarios (crop areas, crop rotations changes, water allocation policy, etc.), could be incorporated into this regional simulation by adjustment of agro-meteorology definition (e.g. Hulme et al., 1992), input parameters (e.g. scenarios-based field management practices), and integration with other regional models (e.g. hydrological model) to achieve an integrated assessment of climate change impacts on rice production rather than on rice yield.

For regional simulations, Hansen and Jones (2000) has summarized the causes of uncertainties due to representative input parameters, and introduced some approaches for reducing bias such as sampling input variability in geographic or probability space (sampling simulation), and calibration of model inputs or outputs (output calibration). Jagtap and Jones (2002) introduced a grid-specific yield correction approach which can effectively correct bias in simulated yields through adjusting the output by a yield correction factor. For climate change impacts and adaptation assessment, because of the lack of information about future agricultural management, sampling simulation might be a useful and effective approach to facilitate adaptation presentation. Because this study focused on input calibration through spatial agreement between observed and simulated values, the calibrated result, which illustrate a current management scenario, might be used as a starting points for sampling simulation to address the adaptation issues.

5. Conclusions

A cross calibration process based on experimental data, agroecological zones and 50 km × 50 km grid scale geographical database was developed for the CERES-Rice model for climate impact studies. Representative model input parameters, including variety parameters and management practices, were determined by minimizing the RMSE of simulated and observed values. This approach was evaluated using either the experimental, or historical agricultural census data at the county level aggregated to 50 km × 50 km grid resolution, compatible with the simulation resolution.

The results show that the cross calibration is suitable for climate impact studies given its limited experimental data requirement and usage of an agro-ecological zone classification to disaggregate parameters values and management practices. But the method only provides and estimates potential production rather than actual agricultural production. The method can be adapted for climate change impacts assessment at a national scale by incorporating other factors (e.g. land use, technology progress, etc.) with the input parameters, and provides an easy way to measure the uncertainties associated with the crop model and its input data.

Simulations showed that the site calibrated CERES-Rice can captures the spatial variation of rice production across most production areas in China. However, the simulation of interannual variation in yield is less realistic, with only 14.4% of the simulated grid series producing significant correlations with observed yields. Further work is necessary to better explain the causes of observed variability in yield and to incorporate the most important factors in the simulation process. When the cross calibrated representative parameters for the AEZ sub-zones were used, the yield bias increased from 15% (for the site calibrated model, measured by relative RMSE) to 23% (cross calibrated model, measured by relative RMSE), which we ascribe to uncertainties with the use of homogeneous input parameters. When the cross calibration model was used to simulate the actual annual rice production in China at 50 km × 50 km grid scale, the yield bias rose further to 34% (measured by relative RMSE), which we primarily ascribed to uncertainties in the census yield data, crop model, geographical database, and input parameters. Further work should aim to reduce the gap between simulated and actual yields by calibrating the model in some specific areas and calibrating the output to account for other yield loss factors (i.e. disease, insects, weeds, harvest, etc.).

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