Front. Earth Sci. 2012, 6(4): 364–372
DOI 10.1007/s11707-012-0332-0

RESEARCH ARTICLE

Estimating potential yield of wheat production in China based on cross-scale data-model fusion

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Abstract The response of the agro-ecological system to the environment includes the response of individual crop's physiologic process and the adaption of the crop community to the environment. Observation and simulation at the single scale level cannot fully explain the above process. It is necessary to develop cross-scale agro-ecological models and study the interaction of agro-ecological processes across different scales. In this research, two typical agro-ecological models, the Decision Support System for Agro-technology Transfer (DSSAT) model and the Agro-ecological Zone (AEZ) model, are employed, and a framework for effective cross-scale data-model fusion is proposed and illustrated. The national observed data from 36 different agricultural observation stations and historical weather stations (1962–1999) are employed to estimate average crop productivity. Comparison of the two models' estimations are consistent, which would indicate the possibility ofcross-scale crop model fusion.

Keywords DSSAT model, AEZ model, data-model fusion, agro-ecological system

1 Introduction

The agro-ecological system is very complex, given that its response to and interaction with environmental changes occur in multiple scales, which can be exemplified by the response of the physiologic process of individual crops to micro-environmental changes and the adaptation of the crop community to regional and global climate changes. Observation and simulation at a single level cannot fully explain the dynamic response and adaption of the agro-ecological system, especially the interaction between its different levels. Therefore, we must quantitatively express the crop physiologic process and the regional system adaption and then integrate the two processes for a more comprehensive and accurate assessment of the effect of climate change on agro-ecological systems.

Previous studies on the estimation of crop productivity over a large area can be grouped into two categories: crop dynamic models and agriculture ecological productivity models. Crop dynamic models, such as the Decision Support System for Agro-technology Transfer (DSSAT) (Jones et al., 2003) model, simulate the basic ecological mechanisms of physiology and the course of crop growth and development. These models required very detailed input data under homogeneous site conditions. However, complete, reliable, and site-specific primary data are often unavailable, thus preventing the successful and confident application of the DSSAT model. This condition is particularly true for soil, climate, and plant genetic data (Jones et al., 2003). Agriculture ecological productivity models, such as the agro-ecological zone (AEZ) model (Fischer et al., 2008), focus on more simplified bio-physiologic crop simulations. This model considers the restrictions of soil and topography on the production of crops concerned and maximizes the available data. The result of this model can reflect the average productive potentialities of a given crop in a given region for a number of years. Therefore, the AEZ method is suitable for simulations at regional, national, and global scales. Necessarily, the model pays less attention to the specific dynamic processes of crop growth.

Considerable effort has been exerted to extend the application scale and scope of the site-specific crop dynamic model. Geographical Information System (GIS) technology has been employed to generate spatial input data for the DSSAT model (Thornton et al., 1997; Seidl et al., 2001; Heinemann et al., 2002; Timmermann et al., 2002). In addition, researchers have used remote-sensing-based models that assimilate the time series vegetation index of multiple years, such as the Normalized Difference

Received March 31, 2012; accepted May 31, 2012

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Vegetation Index and the Leaf Area Index, into the dynamic model to calibrate the crop yield prediction (Prevot et al., 2003; Liang et al., 2004; Dente et al., 2008; Fang et al., 2008). The Bayesian parameter estimation method has been employed to establish the spatial distribution of different input parameters. For example, Iizumi et al. (2009) and Tao et al. (2009) used the Markov chain Monte Carlo (MCMC) technique to estimate the parameters for a large-scale crop model. Jiang et al. (2009) applied the Windows Bayesian inference using Gibbs Sampling (Lunn et al., 2000), a statistical software for the MCMC method, to examine the effects of soil, topographic, and climate variables on maize yield. However, GIS-based or remote sensing-based up-scaling methods do not consider uncertainty in parameter selection and calculation. The MCMC is computationally expensive, thus limiting its implementation in each grid-cell over a large area.

In this paper, we focus on the complementary features between the DSSAT dynamic crop model and the AEZ agriculture ecological productivity model, including such common parameters as crop genetic adaptability. The stability of crop genetic adaptability parameters within an agro-ecological zone provides an intermediate setting to estimate crop genetic adaptability parameters at the cropping zone level using Bayesian approaches. The availability of genetic adaptability parameters at the cropping zone level enables the application of dynamic crop models in each grid-cell over a large area, allowing the comparison of the results of these two models.

We overcome the basic data constraint in DSSAT up-scaling via data-model fusion between the AEZ database and the DSSAT model. We overcome the constraint involving a lack of observed crop dynamics at the grid-cell level using both Generalized Likelihood Uncertainty Estimation (GLUE) and MCMC at the observation site to obtain a stable estimation of key cultivar adaptability coefficients and by matching cultivars with the two-digit classification of cropping zones. The GLUE and MCMC estimations of cultivar coefficients are based on historical observations at 36 stations distributed nationwide over 20 years (1980 to 1999). This procedure allows the estimation of wheat production potential at the grid-cell level based on the site-specific crop dynamic model of DSSAT. This up-scaling estimation is implemented every year from 1962 to 1990 for both irrigated and rain-fed conditions. A comparison between these up-scaling results and the AEZ modeling results are highly consistent in the major wheat production areas of China.

2 Materials

2.1 Crop models

The DSSAT model was originally developed by the International Benchmark Sites Network for the Argo-technology Transfer project. The model simulates the growth and development of crops within a homogeneous plot on a daily time step, and the crop yield is computed on the harvest day (Jones et al., 2003). The core of DSSAT is the cropping system model (DSSAT-CSM), which can simulate over 20 crops and has been widely used to simulate the collective effects of crop genetics, management practices, weather, and soil conditions on crop growth, development, and yield worldwide (Bannayan et al., 2003; Lobell et al., 2005; Lobell and Ortiz-Monasterio, 2006; Timsina and Humphreys, 2006; Xiong et al., 2008). The required input data for the DSSAT model are daily climate data, crop management information, detailed soil data, and the crop cultivar parameters.

The AEZ model was jointly developed by the International Institute for Applied Systems Analysis (IIASA) and the Food and Agriculture Organization (FAO) (Fischer et al., 2008). This model uses regional representations of climate, critical soil, and geographical factors, as well as detailed agronomic-based knowledge, to simulate land resource availability, farm-level management options, and crop production potentials (Fischer et al., 2008). The AEZ model has been validated for use in agriculture resource assessment and has been employed in numerous studies, both regionally and globally (Fischer et al.,2008).

2.2 Data preparation

Observed daily climate data (from 1962 to 1999) from over 700 meteorological stations nationwide were employed (provided by the Chinese Meteorological Data Center), including minimum and maximum air temperature, sunshine hours, precipitation, relative humidity, and wind speed for both models. Solar radiation was calculated using empirical global radiation models based on observed daily sunshine hours (Pohlert, 2004).

Crop management information is critical to crop growth simulation and varies significantly across locations. Observation data are rarely available at the farm-level. Given that this study focuses on potential crop productivity, ideal field management (meaning fully irrigated, well fertilized, no pest impact) was applied. For GLUE and MCMC estimations of cultivar coefficients at the observation stations, the observed cropping and growing calendar was strictly followed, and the highest yield achieved was considered the observed value of yield across the observation years. For the up-scaling application of the DSSAT model beyond the stations, an “automatic” sowing setting of the DSSAT model was applied, and the sowing period was between the maximum and minimum observed sowing date.

The Harmonized World Soil Database (HWSD) (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009) was employed for both models. The soil profile parameters required by DSSAT are quite specific, and data gaps occur between HWSD contents and the DSSAT requirements. To fill the gaps, we consolidated other soil databases, such as ISRIC-WISE (Batjes, 2009). We also conducted conversion calculations based on empirical formulas given in the literature (Rawls et al., 1982; Baumer and Rice, 1988; Ritchie et al., 1989; Gijsman et al., 2002, 2007). The global digital elevation map and the derived slope distribution database are linked to the FAO/United Nations Educational, Scientific, and Cultural Organization digital soil map of the world.

The genetic adaptability coefficients in the DSSAT model quantitatively summarize the processes through which a particular genotype responds to environmental factors. If the local or new cultivars have not been previously applied with the crop model, the genetic coefficients should be estimated and then evaluated with reference to the independent observation data before the application of the crop model. We use both the GLUE module (He et al., 2010) in the latest DSSAT model and our MCMC code to estimate the cultivar coefficients. Detailed definitions and applications of GLUE and MCMC are presented in Sect. 3.

Table 1 lists the genetic coefficients of the DSSAT-Wheat model in DSSAT (Jones et al., 2003). P1D, P1V, and P5 determine the timing of phonological events, such as anthesis date and maturity date. G1, G2, and G3 control the yield-related outputs, such as grain yield, biomass, etc. PHINT is not included in the procedure because its value is similar across different cultivars, and it influences both the phonological development and yield. PHINT was assumed to be 95 for all cultivars.

Table 1 Genetic coefficients of wheat for the DSSAT model (Jones et al., 2003)

Code	Definition
P1D	Photoperiod response
P1V	Days, optimum vernalizing temperature, required for vernalization
P5	Grain filling (excluding lag) phase duration
G1	Kernel number per unit canopy weight at anthesis
G2	Standard kernel size under optimum conditions
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions
PHINT	Phylochron interval between successive leaf tip appearances

3 Methodology

The operational steps for the up-scaling of the DSSAT model are as follows: 1) estimation and validation of genetic adaptability coefficients at 36 observation stations using GLUE and MCMC procedures; 2) reclassification of cropping zones based on the spatial relationship between observed cropping practices at the observation stations and the two-digit classification of the cropping zones; 3) simulation of the annual wheat yield dynamics using the DSSAT model with genetic coefficients remaining stable in each of the reclassified cropping zones, under the historical climate conditions from 1962 to 1999; and 4) comparison and cross-validation of the results of DSSAT up-scaling and the AEZ model.

3.1 Wheat cultivar coefficients estimation

Proper parameter estimation would ensure the accuracy of model prediction (Makowski et al., 2002). The key modeling parameters for the up-scaling of the DSSAT model are the crop cultivar coefficients. The GLUE (Beven and Binley, 1992) and MCMC (Hastings, 1970; Brooks, 1998) methods are becoming increasingly popular for model parameter estimation (Campbell et al., 1999). The popularity of GLUE can be largely attributed to its conceptual simplicity, relatively ease of implementation, and its capability to handle different error structures and models without major modifications to the method itself (Blasone et al., 2008). The MCMC would be more accurate than GLUE (He et al., 2010) but considerably more time consuming and difficult to implement.

The main principle of GLUE is to separate the parameter space by generating a large number of parameter values from the prior distribution. Likelihood values are calculated for each parameter set using field observations. We then calculate probabilities: an empirical posterior distribution of the parameters. For each sample value of cultivar coefficients, we run DSSAT and then assess the performance of the sample based on its corresponding likelihood value (i.e., by closeness to the observed flowing day and yield) and thus, its probability. Finally, we select the cultivar coefficient values of maximum probability.

3.2 Cropping zone reclassification

The cropping zone system defines the land use units in AEZ based on climate, soil, and terrain characteristics relevant to specific crop production. In this study, we assumed that cultivar coefficients in each (two-digit) cropping zone are stable and are represented by the coefficients estimated in the observation station within the cropping zone. Given that 36 wheat observation stations and 42 cropping zones are included, with some zones having more than one station, we must reclassify the readily defined cropping zones in the AEZ setting to identify suitable matches between the sub-cropping zones and the cultivars at the observation stations.

The major reclassification steps are as follows: 1) If a station is present in a sub-cropping zone, the cultivar coefficients of the sub-cropping zone are the same as those of the station; 2) If no station is present in a zone, the closest suitable cultivar station is chosen for that zone; and 3) If more than two stations are in one sub zone, the zone is divided based on the county boundary and then reclassified to the closest suitable stations, so that observed data can be fully utilized. The original cropping zones and the reclassified cropping zones are presented in Fig. 1.

4 Results analysis

4.1 GLUE and MCMC simulation comparison

An intuitive evaluation of GLUE results was conducted by running linear regression calculations between the estimated results and the observed values across all 36 observation stations (Fig. 2). The R^2 of the anthesis day for winter wheat and spring wheat are 0.95 and 0.76, respectively. The R^2 of the maturity day for winter wheat and spring wheat are 0.94 and 0.78, respectively. These results suggest that the DSSAT model performs well for wheat. Table 2 further indicates that all slope coefficients are significantly different from zero. More importantly, the coefficients are reasonably close to 1 (indicating that the simulated value is equal to the observed value), the latter being particularly valid for the coefficients of winter wheat. GLUE generally performs better for winter wheat than for spring wheat. In terms of winter wheat, the departure of the slope coefficients from 1 is low for the anthesis day, the maturity day, the grain weight, and the yield.

The relative accuracy of the GLUE and MCMC methods for genetic coefficient estimation is evaluated using the Relative Absolute Error (RAE, in percent, Eq. (1)), measures the departure between the observed (Obs) and the simulated (Simu) values.

$$\frac{RAE = |Obs - Simu|}{Obs \times 100\%,} \tag{1}$$

In the MCMC runs, two likelihood values for the anthesis day and the wheat yield are calculated for each year. Initial genetic coefficient values refer to the hand-calibrated values calculated with the Genotype Coefficient Calculator (GENCALC) module (Hunt et al., 1993). The statistics of the coefficients' posterior distributions are calculated using the samples only after a burn-in of 10000 runs. Finally, the parameter values were sampled randomly from the 95% credible interval of each posterior distribution and only the last 10000 iterations were chosen for reliable results. The mean value was then chosen as the result.

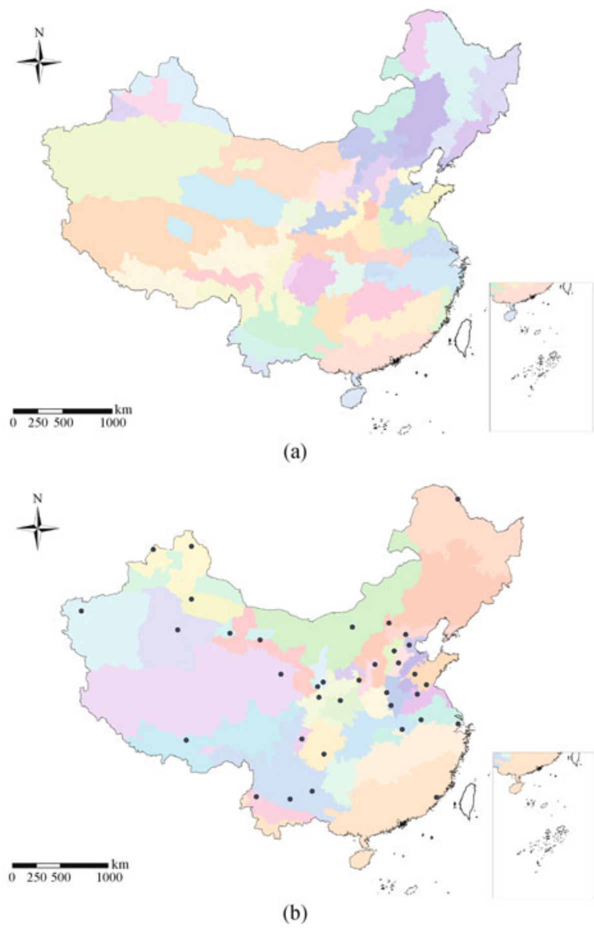

Fig. 1 Reclassified cropping zone map of China based on observation stations. (a) denotes the original cropping zones, (b) denotes the reclassified cropping zones, and the blue points stand for the observation stations

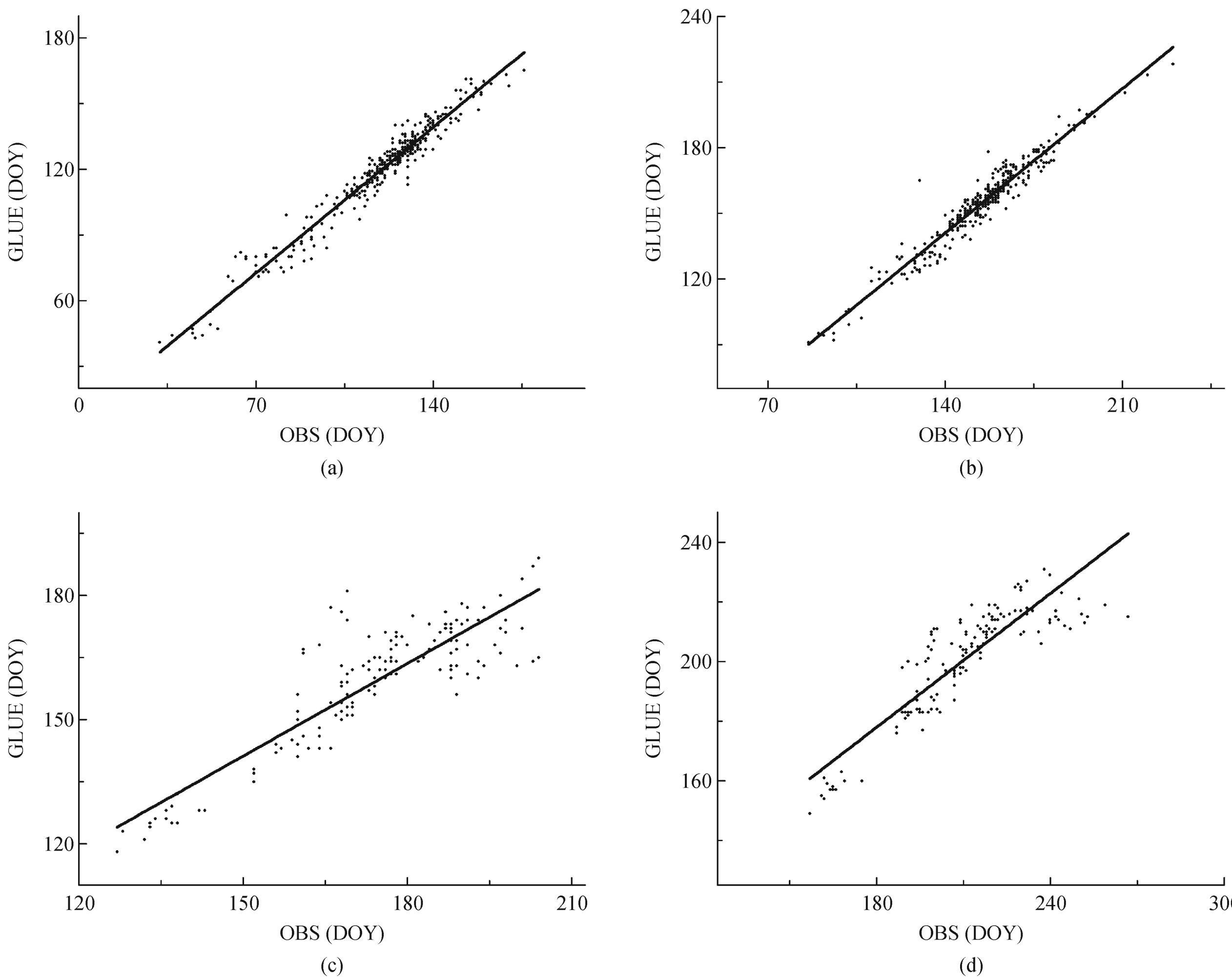

Fig. 2 Comparison between the observed and the GLUE-simulated results (27 winter wheat stations; 9 spring wheat stations) nationwide ((a) and (c) refer to the anthesis day, whereas (b) and (d) denote the maturity day), DOY refers to day of the year

Table 2 Linear regression of simulated versus observed results, slope coefficients and standard errors

Wheat type		Anthesis day	Maturity day	Yield	Unit wt. Grain
Winter wheat	Slope	0.951	0.943	0.931	0.842
	(S.E.)	(0.011)	(0.013)	(0.056)	(0.039)
Spring wheat	Slope	0.746	0.748	0.888	0.913
	(S. E.)	(0.035)	(0.033)	(0.042)	(0.038)

In the GLUE method, 7000 samples were randomly generated for estimation. Two independent procedures are used for the DSSAT implementation: 1) the initial estimation of the phonological development parameters and then that of the growth parameters, with the likelihood values computed for each observation; and 2) the calculation of the probability of each parameter set, after which the set with the maximum probability is chosen.

The RAE values of the anthesis day (DOY, the maturity day (DOY), and the wheat yield (kg/ha) are calculated (Table 3, Fig. 3). The average RAE shows that both methods work equally well. For winter wheat, the average RAE for the anthesis day is 4% versus 6.5%, for maturity day is 2.4% versus 4%, and for grain yield is 14.2% versus 16.7%. Although the performance of the DSSAT model for spring wheat is not so effective, both methods failed to capture the character of the anthesis day and the yield; the RAE values are 10.4% versus 11.6% and 28.4% versus 33.6%, respectively. These results indicate that MCMC performs slightly better than GLUE both for winter wheat and spring wheat, but the method is considerably more difficult to implement and significantly more computa-

Table 3 RAE comparison of wheat simulations using GLUE and MCMC

Wheat type	Station	Anthesis day		Maturity day		Yield	
		MCMC	GLUE	MCMC	GLUE	MCMC	GLUE
Winter wheat	AHHF	4	6.5	2.4	4	14.2	16.7
Spring wheat	FJLH	10.4	11.6	3.7	5.1	28.4	33.6

tionally expensive than GLUE. For application across 36 observation stations, GLUE is more suitable.

4.2 Cross-model validation

Figures 3 and 4 present the average potential wheat yields from 1962 to 1990, as estimated by the AEZ model and by the up-scaled DSSAT model under irrigated (Fig. 3) and rain-fed (Fig. 4) conditions. Maps with the same color-labeling scheme are produced with a resolution of 10 km × 10 km. Figures 3 and 4 show quite similar spatial distribution patterns of wheat yield. This finding is especially valid in the main production regions of the North China Plain and the lower reach of the Yangtze River basin, where the presence of a sufficient number of observation stations guarantees the accuracy of the results. In contrast, the availability of only one observation station in the northern end of the north-east region results in a lower level of yield from the up-scaled DSSAT model compared with the level produced by the AEZ model. In addition, the DSSAT model does not fully incorporate the effect of slope azimuth and gradient, whereas the AEZ model considers these constraints on crop yields. This difference causes higher yield estimation in hilly areas of

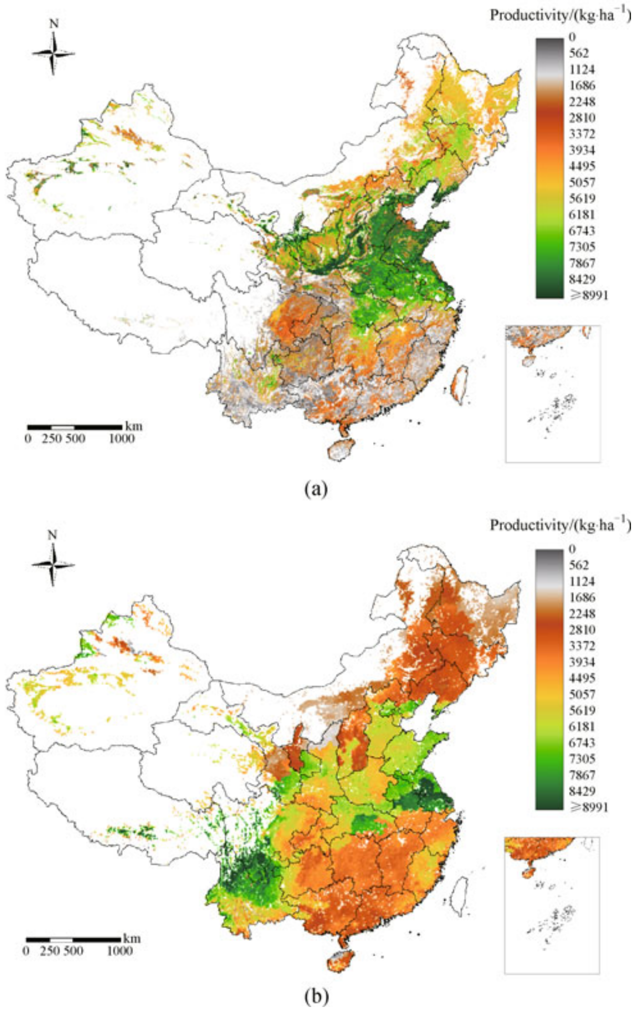

Fig. 3 Average yields (1962 to 1990) on irrigated land, AEZ (a) and up-scaled DSSAT (b)

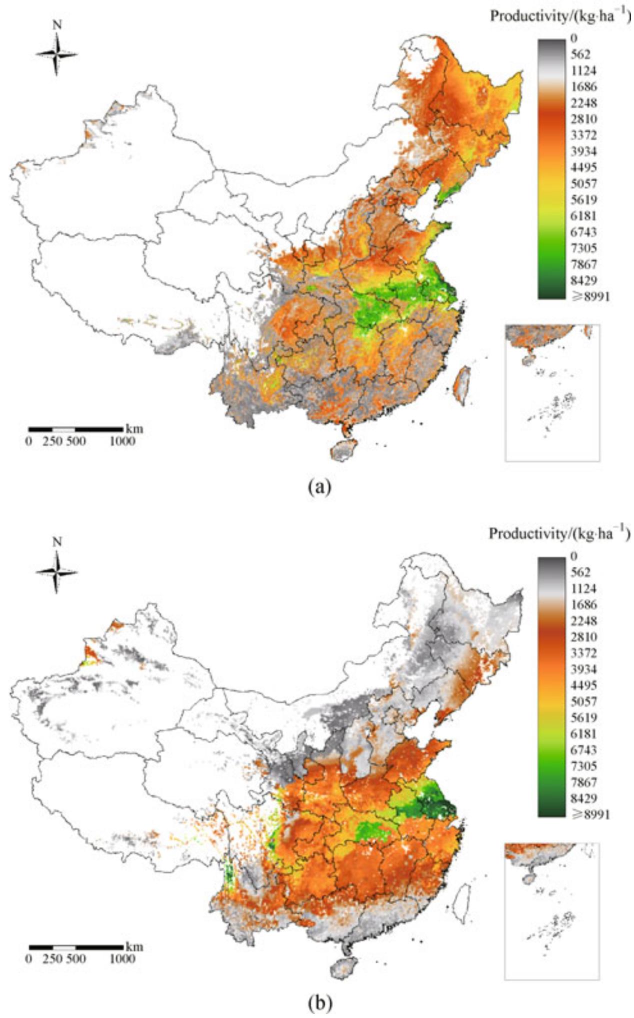

Fig. 4 Average yields (1962 to 1990) on rain-fed land, AEZ (a) and up-scaled DSSAT (b)

the south-west region than that estimated by the AEZ model. Notably, the AEZ model does not perform effectively under the rain-fed conditions in the north-eastern region. Further fusion work is required to improve the performance of the two models.

5 Conclusions and discussion

In this paper, we propose a novel procedure to up-scale one of the most popular site-specific crop dynamic models, DSSAT, directly with the data-model fusion method. The procedure makes the direct application of DSSAT at the regional level feasible.

The major steps employed are as follows: 1) We apply both GLUE and MCMC methods to establish the empirical posterior distribution of crop cultivar coefficients based on a likelihood measure of distance between the model-predicted outcomes and the multi-year observations. Multiple tests indicate that both methods produce stable genetic adaptability parameters. 2) We reclassify the cropping zones of the AEZ model to identify the best match between the observation stations and the cropping zones. This match maximizes scarce crop cultivar data and consequently improves the accuracy of model estimations. The discovery of reliable recorded data from additional observation stations in some specific regions will significantly improve the performance of both DSSAT up-scaling and the AEZ model. 3) We simulate annual wheat yield dynamics using the DSSAT model with genetic adaptability coefficients remaining stable in each of the reclassified cropping zones under the historical climate conditions from 1962 to 1999. The comparison of the estimated yields reveals consistency between the up-scaled DSSAT model and the AEZ model, especially in such major cropping areas as the North China Plain and the lower reach of the Yangtze River basin. However, in the north-east and south-west regions, where wheat is not a major crop, the departure between DSSAT up-scaling and AEZ becomes evident. This difference can be attributed to a lack of observation stations in the north-east (where wheat cultivation is rare) and the lack of full consideration for the effect of slope azimuth and gradient in the hilly areas of the south-west.

A further model of fusion work should include: 1) the improvement of the performance of the AEZ model to enable it to adapt the cultivar coefficient map and other cultivar information produced by the DSSAT up-scaling procedure, and 2) the simplification of the up-scaling procedure of the DSSAT model. To save computing time, the up-scaling procedure must adopt the best crop rotation regimes produced by the agro-climatic assessment of the AEZ model.

Acknowledgements This research was jointly supported by the Open Research Funding Program of Key Laboratory of Geographic Information Science (Ministry of Education), East China Normal University (No. KLGIS2011A11), the National Natural Science Foundation of China (Grant Nos. 40921140410 and 41111140133) and the Climate Change Specific Topic of China Meteorological Administration (No. CCSF2011-12).

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