A Quantitative Knowledge-based Model for Designing Suitable Growth Dynamics in Rice

Dingchun Yan, Yan Zhu, Shaohua Wang and Weixing Cao

(Hi-Tech Key Lab of Information Agriculture of Jiangsu Province, Nanjing Agricultural University, No. 1 Weigang Road, Nanjing, Jiangsu 210095, P. R. China)

Abstract: Quantifying growth dynamics in rice (*Oryza sativa* L.) is important for precision design and diagnosis in cultural management. The primary objective of this study was to develop a general knowledge-based model to design the time-course growth dynamics including stem number, leaf area index (LAI) and aboveground dry matter accumulation with desired target yield under different conditions in rice. Driven by physiological development time (PDT)-based growing degree-days (GDD), the fundamental algorithms of rice growth indices, which vary with the variety, environmental factors and production levels, were formulated from the existing literature and research data. The stem number curve was established according to the dynamic pattern of the stem development and the principle of determining stem number from final panicle number. Under the principle of realizing the maximal photosynthetic production during forty days before and after heading, we obtained the optimum LAI at heading was calculated, and the LAI dynamic from the ratios of LAIs at different growth stages to optimum LAI at heading with linear interpolation method. The aboveground dry matter accumulation curve was described by a logistic curve. Case studies with the typical data sets and variety types at different eco-sites indicated a good performance of the model system, with the root mean square error (RMSE) of $2.5 \times 10^4$ ha$^{-1}$, 0.37 and 700 kg ha$^{-1}$, for the stem number, LAI and aboveground dry matter accumulation, respectively. This model overcomes the weakness of poor spatial and temporal adaptation of traditional rice management patterns and expert systems.

Key words: Dry matter, Expert system, Knowledge-based model, LAI, Rice, Stem number.

Development of decision support system (DSS) provides new tools for quantitative crop management (Cao, 2000). During the past 20 years, many decision-making systems for agricultural production management have been developed by using the knowledge engineering method and information technology (Kline et al., 1988; Lal et al., 1992; Zhu et al., 1998). These systems, normally called expert systems, have been widely used for guiding crop management and generated remarkable social, ecological and economic benefits (Mckinion et al., 1989; Goodell et al., 1990). With the theory of artificial intelligence, the typical expert systems have strong ability to reason and make proper decision for crop management under specific conditions (Plant and Stone, 1991). However, the knowledge rules in traditional expert system contain a large body of expert experience and empirical parameters with site- and time-specific characters (Chai et al., 1994), which has limited the adaptation and accuracy of system decision-making under diverse environmental conditions.

With the principle of system analysis, the simulation model can quantitatively describe and predict the dynamic processes of crop growth, development and yield formation in relation to environmental, genetic and technical factors (Bouman et al., 1996; Sinclair and Seligman, 1996; Priya and Shibasaki, 2001; Andales et al., 2003; Cao and Luo, 2003). Since the simulation models have the functions of system integration and dynamic prediction, the growth model-based decision support systems can recommend management options for user’s choice through a what-if approach (Jones et al., 2003), although the models themselves cannot directly generate optimum decisions on crop production management (Plant and Stone, 1991; Cao and Luo, 2003). Yet, it appears that the concept of dynamic quantification for constructing simulation model could be used for improving the spatial and temporal adaptation of the expert systems. In other words, if the dynamic modeling technology can be used to express the knowledge system for crop management, it would be possible to take advantages of both the crop simulation model and expert system, realizing effective integration of dynamic design and decision making for crop production management.

Rice (*Oryza sativa* L.) is the most important food crop in the world and China. High yield cultivation of rice crop relies on proper design and regulation...
of growth dynamics for a given genotype and environment. The stem number, leaf area index (LAI) and aboveground dry matter accumulation are major indices to describe the growth dynamics of cereal crops, and thus of key importance for guiding cultural regulation and decision-making in crop management (Ying et al., 1998; Lafarge and Hammer, 2002; San-oh et al., 2004). There have been many studies on the time-course patterns of stem number, LAI and dry matter accumulation in rice, along with their quantitative relationships to different cultivars and cultural conditions, driven by growth dynamics and determined by carbohydrate supply of the crop (Rezaul, 1998; Zhong et al., 1999). Several simulation models have been developed for predicting the eco-physiological processes of growth and yield formation in rice under different conditions (Bouman et al., 2001; Meng et al., 2003; Mi et al., 2003). Some investigators further suggested optimal values of key growth characters for the specific rice varieties and conditions by the method of simulation and optimization (Horie et al., 1992). However, existing crop growth models are designed to predict yield formation with detailed processes under a given management package, but not specifically designed to calculate back the desirable growth patterns from target yields, i.e., the desired grain yield. A quantitative knowledge-based model with temporal and spatial mechanisms would be useful for precision designing suitable growth dynamics under a set of defined conditions such as various varieties, environments and production levels.

The main objectives of the present study were to develop a quantitative knowledge-based model for designing proper growth patterns with desired target yield for guiding rice management, and to test if this model could reproduce the recommended growth patterns of rice grown under different conditions. This work would help overcome the weakness of poor spatial and temporal adaptation of traditional expert systems, and lay a foundation for application of the knowledge-based model to precision rice management under various conditions.

Materials and methods

1. Model development

The proposed knowledge-based model for rice management consisted of two major modules for two major functions: design of cultural management plan for general management guideline and design of dynamic growth indices for time-course regulation during the rice growing period, with genotype, climate, soil, and production levels as initial driving factors (Yan, 2004). Among them, the knowledge-based model for design of management planning includes the sub-models for determination of target yield and quality, cultivar choice, sowing date, population density and sowing rate, fertilization strategy, and water management, whereas the knowledge-based model for designing dynamic growth indices consists of the sub-models describing the seasonal progress of major growth characteristics in rice. The main growth indices under the present study include the dynamics of stem number, LAI and dry matter accumulation, and are quantified on the basis of output from the sub-models of target yield, cultivar choice, sowing date, sowing
rate and population density. The structural framework and flow diagram of the knowledge-based model is illustrated in Fig. 1. The sub-models for design of management plan (Yan, 2004) will be detailed in separate publications.

The data used for development of our knowledge-based model were obtained mainly from three sources: (1) literature including research achievements, monographs, books, periodicals, and publications in scientific meetings on rice growth index, along with the records of soil, cultivars and weather data under the study; (2) collaborating scientists in the related research areas; (3) research accumulation, experience and knowledge from the authors group during the past 20 years. Among them, data from (1) and (3) were mainly used for development of the knowledge-based model, and data from (2) were for preliminary evaluation of the knowledge-based model.

Based on induction and extraction of the newest research achievements on rice eco-physiology and cultivation, a conceptual knowledge-based model was established by analyzing and determining the logical relationships of rice growth indices to cultivars, eco-environments and production conditions (Zhu et al., 1998; Yu et al., 2002). By comprehensive analysis of the collected data, we developed the individual algorithms describing the dynamic patterns of rice growth indices in relation to yield target and growing degree-days (GDD). The yield target was designed in a separate sub-model and dependent on yield gap and correction factors from climatic conditions, soil properties and production levels, as detailed by Yan (2004). GDD was based on the physiological development time (PDT), which had been established by our group (Meng et al., 2003).

In principle, the PDT used in the knowledge-based model is a time scale relative to the optimum development environment (Cao and Moss, 1997; Cao and Luo, 2003) so that PDT increment is less than 1 for a given day under normal non-optimum conditions. The daily PDT in rice is equivalent to daily physiological effectiveness (DPE), which is quantified from the interaction of daily photoperiod effectiveness, daily thermal effectiveness and intrinsic earliness of genotype for development progress. The DPE is accumulated to get PDT by a certain stage, as detailed by Meng et al. (2003). It is physiologically assumed that the cumulative PDT required to complete a given developmental phase is constant for normal cultivars under varied temperature and photoperiod conditions. Therefore, the developmental stages of a given rice cultivar under diverse environments can be predicted with the principle of constant PDT requirement for a given stage.

With the PDT as the time scale representing development progress in rice, individual algorithms were developed for describing the dynamic patterns of different growth indices as affected by the main driving factors including cultivars, eco-environments and production conditions, step by step. Then the mathematical algorithms between growth index and driving factors were further integrated into a sub-model of growth index design.

With Microsoft® Visual C++ 6.0 (Kruglinski et al., 1998) as programming language, a preliminary executive knowledge-based sub-model encapsulated in the form of automation with the standard of COM (Component Object Model) was implemented in a computer of PIII 866 CPU and 256M RAM with the operational platform Windows 2000 in Chinese version. This sub-model was further linked with the other sub-models to construct a complete knowledge-based model.

Fig. 2. Time-course changes in daily mean temperature and sunshine during rice growing seasons for a normal year at Nanjing and Shenyang.
based model for rice management (Yan, 2004)

2. Case study on model performance

Case studies were undertaken to test the reliability and applicability of the above knowledge-based model using growth data and weather data under normal climatic years at two eco-sites of Nanjing (118˚48´ E longitude, 32˚03´ N latitude) and Shenyang (123˚25´ E, 41˚08´ N) of China. These two sites were selected because they well represent different rice growing regions in China and there are time-course data of main growth indices as recommended growth patterns for local rice cultivation (Ling, 2000; Wang et al., 2001).

Fig. 2 shows the time-course changes in daily mean temperature and sunshine during rice growing seasons for a normal year at Nanjing and Shenyang.

At Nanjing, daily weather data for the normal year were averages of daily data from 1981 to 1988 provided by Monthly Report of the Ground Meteorology in China compiled by the weather center in Beijing of China, and from 1990 to 1992 and 1994 to 1999 provided by weather station of Jiangsu Academy of Agricultural Sciences in Nanjing. At Shenyang, daily weather data for normal year were averages of daily data from 1981 to 1988 provided by Monthly Report of the Ground Meteorology in China compiled by the weather center in Beijing of China. Daily weather data for normal year includes the daily high and low air temperatures (˚C) and sunlight hours (h). The genetic parameters for the different rice cultivars under evaluation were provided by Nanjing Agricultural University and literature (Ling, 2000; Wang et al., 2001), including Shanyou 63 (Indica hybrid) and Wuyunjing 7 (Japonica) at Nanjing, and Shennong 8718 (Japonica) at Shenyang.

Then, the knowledge-based model was operated to generate theoretical growth dynamics of stem number, LAI and dry matter accumulation under the above conditions. The designed growth patterns were compared with the recommended values or expert values, and the root mean square errors (RMSEs) were calculated to test the fitness and reliability of the model, along with the 1:1 linear plot of the expert values against the designed values (Snyder et al., 1999; Casanova et al., 2000). The smaller the RMSE value, the better the coherence and less the deviation between the designed and expert values. The RMSE can be calculated by the following equation, where EXPi is the expert value, DESi is the designed value, and n is sample number.

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (EXP_i - DES_i)^2}{n}}
\]

Results

1. Description of algorithms

(1) PDT and GDD

The PDT is obtained from a separate sub-model, and used to predict the main developmental stages under different environments, as detailed in Meng et al. (2003). From the predicted stages using the PDT, the GDD (growing degree-days, ˚C·d) at the different stages were calculated with the temperature data as follows:

\[
GDD = \sum (DAT - 10)
\]

Where, DAT (˚C) is daily average air temperature and 10 is the basal air temperature for rice development (Gao et al., 1992).

Then, the PDT-based GDD was used in the following algorithms as a driving time scale to describe dynamic changes of individual growth index over growing progress.

(2) Stem number

Initial seedling density (ISD, 10^4 ha^-1) is the starting point for predicting the suitable population size in paddy rice, which varies with target yield level and can be obtained as the output from a separate module of knowledge-based model system (Yan, 2004). Dynamics of suitable stem number in rice driven by GDD can be quantified by equation 2.

\[
SN(GDD) = ISD + (SN_{max} - ISD) \times e^{-\frac{GDD}{GMSN}}
\]

where, SN(GDD) is stem number (10^4 ha^-1) at a given GDD, ISD is the initial seedling density (10^4 ha^-1), SN_{max} is the maximum stem number (10^4 ha^-1) calculated by equation 3, ICSN is increment coefficient of stem number from equations 8 and 9, and GMSN (˚C·d) is the GDD at the maximum stem number.

\[
SN_{max} = MSPTSN \times ISD
\]

In equation 3, MSPTSN is the maximum single plant theoretical stem number (normally at onset of internode elongation), which can be calculated in two
cases following the general empirical relationships reported by Diao (1997) and Ling (2000).

$$\text{MSPTSN} = \frac{1}{(1+\text{NBT})} \left[ \frac{\text{SN}_{\text{max}}}{\text{SN}_{\text{GDD}}} \right]$$

(1)

In equation 2, the 

$$\text{SN}_{\text{GDD}}$$

is the maximum stem number at the end of the observed date (Diao, 1997), and the accumulation of GDD at the onset of internode elongation (GDE) can be calculated using daily weather data from the predicted onset of internode elongation using the PDT approach. The PDT at the onset of internode elongation (PDTE) is derived from equation 7 (Meng et al., 2003), where INMS is the elongated internode number on the main stem of rice, a variety parameter, and 32 is the PDT value required to reach heading.

$$\text{PDTE} = 32 - 3.2 \times \text{INMS}$$

(7)

For a proper growth pattern without limitation of fertilizer and water, stem number at the critical leaf age for productive tillers (CLAPT, 10^1 ha\(^{-1}\)) should reach the value of final panicle number at maturity (FPN, 10^1 ha\(^{-1}\)), and the ratio of stem number at heading (PDT=32) to final panicle number is about 1.15 as generally recommended (Ling, 2000) and also from our own experience. FPN is calculated by a separate module of the knowledge-based model system and changes with target yield level (Yan, 2004). The leaf age for productive tillering is regarded as termination time for occurrence of productive or effective tillers (Diao, 1997). Thus, the ICSN values in equation 2 before onset of internode elongation (ICSN1) and after onset of internode elongation until heading (ICSN2) can be quantified by equation 8 and 9, respectively. Without limitation of fertilizer and water, the proper stem number should keep decreasing until reaching a constant final ear number, and in this course about 13% of tillers would become non-productive. For a simpler model, the tiller dynamics between heading and maturity can be described by a linear equation.

$$\text{ICSN1} = -\ln\left(\frac{\text{FPN}_\text{ISD} - \text{ISD}}{\text{SN}_{\text{max}} - \text{ISD}}\right) \times \frac{GDD_{\text{H}}}{GDD_{\text{C}} - GDD_{\text{H}}}$$

(8)

$$\text{ICSN2} = -\ln\left(\frac{\text{FPN} - \text{ISD}}{\text{SN}_{\text{max}} - \text{ISD}}\right) \times \frac{GDD_{\text{H}}}{GDD_{\text{C}} - GDD_{\text{H}}}$$

(9)

In equation 8~9, GDDC (°C·d) and GDDH (°C·d) are GDDs at critical leaf age for productive tiller (PDT=13) and heading (PDT=32), respectively, at a normal planting density, and can be calculated through PDT approach (Meng et al., 2003) using daily weather data.

(3) LAI

Under a proper growth pattern with normal planting density in rice, the LAI at the stage of critical leaf age for productive tiller (PDT=13), onset of internode

| Decision site | Variety name         | Initial seedling density (Measured, 10^4 ha\(^{-1}\)) | Yield target (Calculated, kg ha\(^{-1}\)) | Thousand grain weight (Measured, g) | Germination ratio (Measured) | Seedling survival ratio (Measured) |
|---------------|----------------------|-----------------------------------------------|-----------------------------------------|------------------------------------|-----------------------------|----------------------------------|
| Nanjing       | Shanyou 63           | 70                                            | 9750                                    | 28                                 | 0.90                         | 0.90                             |
|               | Wuyunjing 7          | 117                                           | 11700                                   | 26                                 | 0.90                         | 0.90                             |
| Shenyang      | Shennong 8718        | 81                                            | 9000                                    | 27                                 | 0.85                         | 0.85                             |

1) Soil types for Nanjing and Shenyang are all Gleyed paddy soil (Alfi sols for U.S. taxonomy), and 150 kg ha\(^{-1}\) N (as urea), 120 kg ha\(^{-1}\) P\(_2\)O\(_5\) (as monocalcium phosphate [Ca(H\(_2\)PO\(_4\))]\(\_2\)), and 120 kg ha\(^{-1}\) K\(_2\)O (as KCl) were applied and incorporated before transplanting, nitrogen as urea was also applied at onset of internode elongation (70 kg ha\(^{-1}\)) and boosting (50 kg ha\(^{-1}\)).

2) Germination ratio refers to the ratio of germinated seeds to seed number, which is influenced largely by moisture and pests.

3) Seedling survival ratio refers to the ratio of survival plants to germinated plants, which is influenced largely by water and pests.
elongation (PDT=PDTE, Eq. 7) and maturity (PDT=57) (Meng et al., 2003) are about 0.25, 0.55 and 0.35 times of the maximum LAI at heading, respectively, according to the general recommendation for proper rice culture (Diao, 1997; Ling, 2000). Thus, using PDT-based GDD as time scale, the suitable LAI dynamics under high yielding conditions (SLAI_{ym}(GDD)) can be quantified with linear interpolation from the ratios of LAI at different stages to the maximal LAI at heading (MLAI) using the following equations (10-16), and the suitable LAI dynamics for the specific target yield (SLAI_{yt}(GDD)) can be obtained by modifying SLAI_{ym}(GDD) with target yield.

The basis for determining the suitable LAI at heading is to realize that the maximum photosynthetic production is highest during the 40 days before and after heading (Gao et al., 1992). Thus, the mean light intensity at the lower canopy (MLILC, $\mu$mol m$^{-2}$ s$^{-1}$) at heading should be equal to daily light compensation point. The daily light compensation point is the light intensity when the daily photosynthetic production is equal to the sum of daily light and dark respiration, i.e. daily net photosynthesis is equal to daily dark respiration. Thus, the MLILC ($\mu$mol m$^{-2}$ s$^{-1}$) can be calculated by equations 10-12:

$$\text{MLILC} = \text{B} \times \text{CLIRL} \quad (10)$$

$$\text{B} = \frac{(24 - \text{DL}) \times \text{RRND} + \text{DL}}{\text{DL}} \quad (11)$$

$$\text{RRND} = \frac{\text{ATN} \times \text{ATD}}{\text{TCR} \times \text{DL}} \quad (12)$$

where, CLIRL ($\mu$mol m$^{-2}$ s$^{-1}$) is the compensating light intensity of rice leaves, about 20 $\mu$mol m$^{-2}$ s$^{-1}$ (Gao et al., 1992); B is the intermediate variable; DL is day length (h) calculated by the method of Zhu et al. (2002); RRND is the ratio of respiration during night and daytime due to the diurnal temperature difference; TCR is the temperature coefficient of maintenance respiration, commonly equal to 2 (Gao et al., 1992); ATN and ATD are the average temperatures (°C) during night and daytime, respectively.

Based on Monsi and Saeki (1953) formula on the relationship between leaf area index and canopy light attenuation, the maximal LAI at heading (MLAI) can be quantified by equation 13.

$$\text{MLAI} = \ln \left(\frac{\text{MLILC}}{\text{HNSI}}\right) \times \frac{1}{\text{CLEC}} \quad (13)$$

where, CLEC is the canopy light extinction coefficient at heading and can be calculated by equation 14 (Diao, 1997); HNSI ($\mu$mol m$^{-2}$ s$^{-1}$) is the horizontal natural sunlight intensity above canopy and can be obtained from equation 15-16 (Zuo,1991).

$$\text{CLEC} = \sin(\text{ALIAPTTL}) \quad (14)$$

$$\text{HNSI} = \text{SIAL} \times (0.25 + 0.45 \times \frac{\text{DSH}}{\text{DL}}) \quad (15)$$

In equation 14, ALIAPTTL is the average leaf inclination angle of plant top 3 leaves, and is determined as the angle of attachment of the leaf blade to the leaf sheath and the curvature of the leaf blade, normally at 25~30° (Diao, 1997), a variety-specific parameter.

In equation 15, DSH is the daily sunshine hour (h) provided by daily weather data; the values of 0.25 and 0.45 are empirical parameters; SIAL ($\mu$mol m$^{-2}$ s$^{-1}$) is the sunlight intensity above atmosphere layer, and can be calculated with the Julian day (JD) by equation 16:

$$\text{SIAL} = 140000 (1.0 + 0.033 \cos(\frac{2 \pi \text{JD}}{365})) \quad (16)$$

Fig. 3. Designed and recommended dynamics of stem number for different varieties at two eco-sites, Shenyang and Nanjing.
Then, the SLAI_{yt}(GDD) can be calculated by modifying SLAI_{ym}(GDD) with target yield in equation 17.

In the above equation, GDDH and GDDM are the accumulated GDDs at heading and maturity; YT is the desirable grain yield designed for a set of cultural conditions (kg ha\(^{-1}\)) and dependent on yield gap and correction factors from climatic conditions, soil properties and production levels; YM is the maximal grain yield achievable at the decision site with neither fertilizer nor water limitation (kg ha\(^{-1}\)). Both YT and YM were obtained from a separate yield design module (Yan, 2004). We assumed that SLAI_{yt}(GDD) ranges between 50% and 100% of SLAI_{ym}(GDD) and 0.5 is the parameter for determining the minimum SLAI_{yt} value.

(4) Dry matter accumulation

The progress of dry matter accumulation in rice exhibits the pattern of the logistic curve, which can be quantified by equation 18:

\[
\text{DMA(GDD)} = \frac{\text{MDMA}}{1 + \text{CDDMIS} \times e^{-\text{IRDM} \times \text{GDD}}} \]  

where DMA(GDD) is dry matter accumulation (kg ha\(^{-1}\)) at a given GDD, MDMA (kg ha\(^{-1}\)) is the maximum dry matter accumulation at the maturity and can be calculated from equation 19, CDDMIS is the constant determined as the dry matter at the initial stage and can be derived from equations 20 and 21, and IRDM is the increasing rate of dry matter and can be obtained from equation 23.

As shown by equation 18, when GDD is approaching infinity (in fact, limited by phenology), DMA would be equal to MDMA. Therefore, MDMA can be approximately expressed by the dry matter accumulation at maturity with equation 19.

\[
\text{MDMA} = \frac{\text{YT}}{\text{HI}} \]  

where HI is the harvest index as cultivar-specific parameter, and YT (kg ha\(^{-1}\)) is the yield target designed with a separate module (Yan, 2004).

Also, when GDD is zero, DMA is equal to MDMA/(1+CDDMIS). About 92% of the nutrition matter (embryo and endosperm) in rice seed provides nutrition for the early rice growth (Diao, 1997), so CDDMIS can be derived from equation 20 and 21.

\[
\text{CDDMIS} = \frac{\text{YT}/\text{HI}}{0.92 \times \text{SR}} \times 100 \]  

\[
\text{SR} = \frac{\text{ISD} \times \text{TGW}}{\text{GR} \times \text{SSR} \times 100} \]  

where, SR is sowing rate per unit area (kg ha\(^{-1}\)) calculated by initial seedling density (ISD, 10\(^2\) ha\(^{-1}\)),

Fig. 4. Designed and recommended dynamics of LAI for different varieties at two eco-sites, Shenyang and Nanjing.
thousand grain weight (TGW, g), germination ratio (GR, 0 ~ 1) and seedling survival ratio (SSR, 0 ~ 1).

Rice grains are formed and filled after anthesis, with the filling matter from two sources, one is the matter reserved in the vegetative organs before anthesis, and the other is the post-anthesis photosynthetic production. Literature (Diao, 1997; Ntanos and Koutroubas, 2002) indicated that the dry matter accumulation from the post-anthesis photosynthetic production accounted for about 38 ~ 43.8% of the total dry matter accumulation at maturity for a proper rice growth. Thus, the pre-anthesis dry matter accumulation (PDMA, kg ha$^{-1}$) can be calculated by equation 22, where the value of CFPPP (0 ~ 1) is the contribution fraction of post-anthesis photosynthetic production for grain yield, and could be the average value for a given production system, or individual value for a specific cultivar and cultural management.

$$ PDMA = \frac{YT}{HI} \times \left(1 - CFPPP \right) \tag{22} $$

Then, IRDM in equation 18 can be calculated by equation 23, where GDDH is the GDD required for heading, and the MDMA, PDMA, and CDDMIS can be calculated respectively by the same procedure mentioned above.

$$ IRDM = -\ln\left(\frac{MDMA-PDMA}{PDMA \times CDDMIS}\right)/GDDH \tag{23} $$

2. Performance of model

To evaluate the reliability of the knowledge-based model, we carried out case studies on stem number, LAI, and dry matter accumulation in rice by comparing the model-designed growth dynamics with the recommended growth data at different eco-sites, Nanjing and Shenyang, and different cultivars under a normal climatic year. Table 1 shows the characteristic variety parameters, and Table 2 shows the basic cultural parameters. The time-course climate change patterns shown in Fig. 2, show that the daily mean temperatures during rice growing season were consistently higher at Nanjing than at Shenyang. The accumulative temperatures above 10°C in a year were 2757.9°C at Nanjing and 1835.6°C at Shenyang, about 34% difference between the two sites.

Fig. 3-5 shows the growth dynamics of stem number, LAI, and dry weight, respectively. The model designed curves well agreed with the recommended or expert values, with the RMSE of $2.5 \times 10^4$ ha$^{-1}$, 0.37 and 700 kg ha$^{-1}$, respectively, for stem number, LAI, and dry weight, respectively. Overall, the stem number gradually increased from the start of tillering, reached maximal values at onset of internode elongation, and then began to decrease until maturity with final panicle numbers (Fig. 5). However, the growth dynamics of stem number varied with different climatic conditions, with earlier and higher peak at Shenyang than at Nanjing. The LAI increased quickly after transplanting, reached maximal at heading, and then decreased until maturity. The maximal LAIs varied with the rice cultivar and climatic condition (Fig. 4), with higher values at Nanjing than at Shenyang. The dry matter accumulation in rice increased following the pattern...
of Logistic curve, with small changes at the beginning, fast increases after onset of internode elongation, and maximal values during booting and filling (Fig. 5). The dynamics of dry matter accumulation with different cultivars varied with different genetic characters of the cultivars, and the total amount of dry matter accumulation decreased with enhanced harvest index.

The above results of the case studies on the stem number, LAI, and dry matter accumulation in rice indicated that the time-course curves of stem number, LAI, and dry matter accumulation designed by the knowledge-based model for two eco-sites and different cultivars are overall in good fit with the recommended growth dynamics for the local conditions (Ling, 2000; Wang et al., 2001), and also consistent with general growth patterns in other literature (Diao, 1997). Thus, it can be considered that the present knowledge-based model has a good performance for quantitative design and diagnosis of the growth dynamics in cultural management of rice.

**Discussion**

Based on the cultural theories and techniques in rice, a quantitative knowledge-based model for designing dynamic growth indices with the characters of spatial and temporal applicability was developed by quantifying the relationships of rice growth and development characters to cultivar traits, environmental factors and production conditions. The model was composed of the algorithms for describing the time-course patterns of major growth indices in rice using stem number, LAI, and dry matter accumulation, driven by PDT-based GDD scale. Case studies at different eco-sites and with different cultivars showed that the dynamics of growth indices designed by the knowledge-based model are well consistent with the recommended growth data under normal conditions, implying a good performance of the model system in designing a proper cultural pattern. This work provides a quantitative tool for determination of growth dynamics for desired grain yield in rice under different conditions.

The present knowledge-based model for quantifying the growth dynamics at the target grain yield in rice has integrated the decision-making function of expert systems and the dynamic prediction function of simulation models for constructing a digital expert system in precision crop management. The knowledge-based model can be considered as a set of algorithms with temporal and spatial characters for designing of proper dynamic growth indices for time-course regulation criteria during rice growing period. In nature, it’s a modeled or digitalized expert system for optimum decision-making on rice management (Cao and Luo, 2003), rather than a simulation model for real-time prediction of rice growth status on the what-if cycle from a given set of conditions (Bouman et al., 1996; Cao and Moss, 1997). In principle, the dynamic rice growth indices from the knowledge-based model can be used as ideal growth curves or indicators for guiding cultural management and regulation of crop growth system to obtain target grain yield (Cao and Luo, 2003; Zhu et al., 2002). This also implies that the knowledge-based model should be evaluated as a type of expert system with emphasis on practical application value for precision design and diagnosis of dynamic growth index in cultural management of rice crop.

Compared with the traditional management expert system for designing growth index (Goodell et al., 1990; Plant and Stone, 1991; Chai et al., 1994), the present knowledge-based model used PDT as a predictor of developmental progress with the principle of constant PDT for a given stage (Meng et al., 2003; Zhu et al., 2002), then calculated the GDD from the PDT required to reach different stages, and finally established the dynamics of growth index on the basis of dynamic GDD scale. The stem number curve was developed according to the dynamic pattern of the tillering and development and the principle of determining tiller number from the final panicle number. Under the principle of realizing the maximal photosynthetic production during the 40 days before and after heading, we calculated the suitable LAI at heading by Monsi formula, and then obtained the LAI dynamic from the ratios of LAIs at different growth stages to the maximal LAI at heading by the linear interpolation method. The dry matter accumulation curve was established with the logistic curve. These fundamental algorithms make the knowledge-based model more explanatory and applicable to various environments, genotypes, and growth stages, thus overcoming the weakness of poor spatial and temporal adaptation of the traditional rice management patterns and rule-based expert systems. The results of model testing further proved high accuracy and reliability of the knowledge-based model system under different conditions.

Compared with the growth model, the present knowledge-based model was developed specifically to design the growth indices from the desired target yield with reasonably limited number of environmental variables. Although a growth model-based decision-support system can be used for this purpose, a crop growth model generally requires more input variables and complex calculation, which is often difficult to implement and may cause obvious errors from the what-if simulation cycles. On the other hand, all growth indices are supposed to be dependent on each other, i.e., tiller dynamics will affect leaf area, which in turn affects light interception and biomass growth. These interrelations can be easily incorporated into a process-based crop growth model, but hard to be quantified in the present knowledge-based model which is not based on growth processes. In addition,
the simulation model is normally tested for the goodness of fit between observation and prediction for any simulation scenarios, but the knowledge-based model can be evaluated directly for practical decision-making ability in precision crop management.

Since the present work is the first effort to create a quantitative knowledge-based model, its methodology is still immature and its contents remain to be improved in the future research and practice. In particular, carefully designed experiments are needed to refine the algorithms and expand the dynamic indices for comprehensive and accurate design of inter-related growth indices under various conditions and genotypes. For instance, the present knowledge-based model was designed to be applicable to normal production conditions, and some parameters were fixed as cultivar-specific values, which may change under extreme conditions such as temperature and nutrient stress and deep water flooding. The changes in tiller number and LAI under sub-optimum yield levels need more accurate algorithms in relation to yield factor. Also, more comparative field experiments should be conducted with the model-designed growth dynamics and recommended growth indices or expert patterns under different eco-sites and production levels so that the application value of the knowledge-based model can be widely tested and necessary improvement made. Further studies are necessary to see how the gap between the designed and actual growth indices will help improve the management practices and optimize growth performance. These processes would enhance the reliability and usefulness of the model system for recommending rice growth patterns at desirable target yield in future digital farming.

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*In Chinese.

**In Chinese with English abstract.
Appendix: The abbreviated variables and their description used in the present paper.

| Variable   | Description                                                                 | Unit          |
|------------|-----------------------------------------------------------------------------|---------------|
| ALIAPTTL   | average leaf inclination angle of plant top 3 leaves                         | °             |
| ATD        | average temperature during daytime                                           | °C            |
| ATN        | average temperature during night                                             | °C            |
| CDDMIS     | constant determined as the dry matter at the initial stage                  | kg ha⁻¹       |
| CFPPP      | contribution fraction of post-anthesis photosynthetic production for grain yield |              |
| CLAPT      | critical leaf age for productive tiller                                     |               |
| CLEC       | canopy light extinction coefficient                                          |               |
| CLIRL      | compensating light intensity of rice leaves                                 | µmol m⁻² s⁻¹ |
| COM        | component object model                                                       |               |
| DAT        | daily average air temperature                                                | °C            |
| DL         | day length                                                                  | h             |
| DMA(GDD)   | dry matter accumulation at a given GDD                                      | kg ha⁻¹       |
| DPE        | daily physiological effectiveness                                            |               |
| DSH        | daily sunlight hour                                                          | h             |
| DSS        | decision support system                                                      |               |
| FPN        | final panicle number at maturity                                             | 10⁴ ha⁻¹      |
| GDD        | growing degree-days                                                         | °C·d          |
| GDDC       | GDD at critical leaf age for productive tiller                             | °C·d          |
| GDDE       | GDD at onset of internode elongation                                         | °C·d          |
| GDDH       | GDD at heading                                                              | °C·d          |
| GDDM       | GDD at maturity                                                              | °C·d          |
| GR         | germination ratio                                                           | 0–1           |
| GMSN       | GDD at the maximum stem number                                               | °C·d          |
| HI         | harvest index                                                               |               |
| HNSI       | horizontal natural sunlight intensity above canopy                           | µmol m⁻² s⁻¹ |
| ICSN       | increment coefficient of stem number                                         |               |
| ICSN1      | ICSN value before onset of internode elongation                             |               |
| ICSN2      | ICSN value after onset of internode elongation until heading                |               |
| INMS       | elongated internode number on main stem                                      |               |
| IRDM       | increasing rate of dry matter                                                |               |
| ISD        | initial seedling density                                                     | 10⁴ ha⁻¹      |
Appendix (continued).

| Acronym | Description |
|---------|-------------|
| IV      | intermediate variable |
| JD      | Julian day |
| LAI     | leaf area index |
| LAITT   | leaf age at initial tillering time in rice under direct seeding and small seedling transplanting conditions |
| LAST    | leaf age at seedling transplanting |
| TLNMS   | total leaf number on main stem |
| MDMA    | maximum dry matter accumulation at maturity kg ha⁻¹ |
| MLAI    | maximal LAI at heading |
| MLILC   | mean light intensity at lower canopy μmol m⁻² s⁻¹ |
| NBT     | number of big tillers with over 3 own leaves |
| NLEPT   | number of leaves emerging on productive tillers |
| SLAIₘₐₚ(GDD) | suitable LAI dynamic under maximal yield conditions at a given GDD |
| SLAIₘₛ(GDD) | suitable LAI dynamic under specific target yield at a given GDD |
| PDT     | physiological development time |
| PDTE    | PDT at onset of internode elongation |
| PDMA    | pre-anthesis dry matter accumulation kg ha⁻¹ |
| RMSE    | root mean square error |
| RRND    | ratio of respiration during night and daytime |
| SIAL    | sunlight intensity above atmosphere layer μmol m⁻² s⁻¹ |
| SN(GDD) | stem number at a given GDD 10⁴ ha⁻¹ |
| SNₘₐₓ | maximum stem number 10⁴ ha⁻¹ |
| MSPTSN  | maximum single plant theoretical stem number |
| SR      | sowing rate per unit area kg ha⁻¹ |
| SSR     | seedling survival ratio |
| TCR     | temperature coefficient of maintenance respiration |
| TGW     | thousand grain weight g |
| YM      | maximal grain yield achievable at decision site without fertilizer and water limitation kg ha⁻¹ |
| YT      | target grain yield designed for a set of cultural conditions kg ha⁻¹ |