Regional application of the site-specific biochemical process-based crop model DNDC for rice in NE-China

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Abstract: Biochemical process-based crop models are extensively applied in agro-ecosystem research due to their capability of estimating crop parameters and agro-environmental factors. To better understand the interactions among agro-ecosystem factors, it is essential to consider spatial variability. As a biochemical process-based crop model, DNDC (DeNitrification-DeComposition) simulates the biogeochemical cycles of carbon and nitrogen. It consists of six sub-models: soil-climate, plant growth, decomposition, nitrification, denitrification and fermentation.

In this study, the DNDC model is applied for paddy rice yield estimation on the regional scale in 2009. The study area Qixing Farm, covering an area of 120,000 ha, is part of the Sanjiang Plain located in Heilongjiang Province, Northeast China. On about 50,400 ha paddy rice is cultivated. At eleven field test sites, the crop status during different phenological stages was measured. Farm management practices including tillage, fertilizer application and irrigation were also recorded. After the crop season, yield data information from 60 farmers all over Qixing Farm was collected.

The DNDC model supplies two operating modes, the site-specific mode and the regional mode. In the regional mode, the whole research area is divided into small subunits which are assumed to have the same model inputs. Subsequently, the model results from all these units are merged to obtain a regional result. In this way, the spatial variability of the study region is not sufficiently considered. Additionally, the regional mode is not as flexible and transparent as the site-specific mode because less parameters can be set by the user.

It is well recognized that the quality of the spatially distributed model input data for soil, management, and weather plays a key role for crop modelling on regional scales. In this study, the input datasets for the model were generated in a two-step process: First, the input data that can be assumed to be homogeneous for the whole study region (e.g. weather data) were organized according to the classic DNDC model input format. Secondly, the datasets with a high spatial variability such as the soil data were prepared in raster format. In order to detect within-field variability in the study region, but to keep the computation time reasonable, raster datasets with a pixel size of 100 × 100 m were prepared as model inputs. Pixels of all generated raster datasets were snapped/registered to a standard raster (soil type map) dataset. To be able to use these raster datasets in the context of DNDC's site-specific mode, additional scripting was necessary. A script was developed that automatically creates the DNDC model input file for each of the 100 × 100 m raster pixels in the study region by combining the values of each individual pixel with the static part generated in the first step. An additional script was created to automatically generate raster output files out of the ca. 100,000 result files. For each output parameter of the model, a separate raster map is generated.

The soil parameters are one of the most sensitive factors in the DNDC model. Therefore the soil property maps were generated in form of raster files as model inputs. Datasets of soil physical properties (e.g. soil texture) in raster format were produce based on the soil type map which provided by the Chinese Agricultural Academy of Sciences. The soil nutrient information, which is assumed not to be as stable as the physical properties, was

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measured (in 2007 and 2008) and provided by the Qixing Farm Research Center. These point data were processed to generate the raster-based model input file by implementing a Kriging interpolation approach. Weather datasets and crop management datasets were prepared in the classic model input format.
Modelled results of regionally appling the site-specific mode are presented as rice yield maps for the Qixing Farm.

1. Introduction

In agro-ecosystem research, process-based crop models are extensively applied. Plant development and growth are calculated as a function of environmental parameters and agricultural management data. The many existing crop models are mainly characterized by 1) the crop type(s) considered, 2) the degree of complexity regarding the modelled processes, 3) required input data, 4) the temporal resolution of modelled processes (model time step) and of course 5) the main application aim.
For this study, the DeNitrification-DeComposition (DNDC) model (developed by LI et al. 1992, modified by LI et al. 2000, 2007) was chosen in order to test the model capability for detecting within-field variability in paddy rice yield for a study area in Northeast-China. The overall aim is to analyze agro-environmental patterns of spatial variability in the context of precision agriculture.
The DNDC model simulates the carbon and nitrogen biogeochemical cycles and is composed of the following six interacting sub-models: soil-climate, plant growth, decomposition, nitrification, denitrification and fermentation. In several studies, the DNDC model was applied for paddy rice fields in China (e.g. LI et al. 2002, ZOU et al. 2009, ZHANG et al. 2014). The DNDC model is one of the few process-based crop models for which both a site-specific mode and a regional mode were developed. In the regional mode, the research region can be divided into small subunits based on the assumption that the attributes in each unit are uniform. The model merges the results from all units to obtain a regional result. Compared to the regional mode, the site-specific mode is assumed to be more flexible and transparent (PERLMAN et al. 2013), attributing this fact to its capability of specifying detailed model inputs such as management practices which include the number, amount and type of the fertilizer applications.
Data quality is one of the most important factors that determine the final results in the study of agro-environmental ecosystems (BARETH 2009). In a regional study, model inputs with sufficient approximations of spatial variability were found to be essential to obtain satisfying model results (ZHANG et al. 2014). For the aim of this study, soil input data with a high spatial resolution to depict within-field heterogeneities are needed. Therefore, the DNDC site-specific mode was adapted to model paddy rice growth with a pixel size of 100 m × 100 m on the regional scale of the Chinese Qixing Farm (120,000 ha) in the year 2009.
In this study, (1) spatially detailed soil input data were prepared in form of raster datasets, and (2) the site-specific mode of the DNDC model (version 9.5) was adapted for regional applications by creating additional scripts to automatically assimilate raster datasets as model input data.

2. Study area

The study was conducted for the Qixing Farm (47.2° N, 132.8° E), a national farm located in the central part of the Sanjiang Plain (SJP), Northeast China. The SJP is an alluvial plain formed by the Songhua River, the Heilong River and the Wusuli River. The climate of the SJP is temperate sub-humid, with a mean annual precipitation of 500–650 mm. Rainfall mainly occurs from May to September during the growing season of crops. The accumulated ≥ 10 °C temperature all across the year is about 2300–2500 °C and only single-season crops are planted. The topography of the SJP is fairly flat with an average elevation of 60 m. Rice is one of the main crops in this area.

3. Material and Methods

3.1 Data description

3.1.1 Meteorological input data

According to the input data requirements of the DNDC model, meteorological data with a daily temporal resolution are needed. Daily measurements for the year 2009 were provided by a local meteorological station, situated in the study area. Input data of maximum and minimum temperature, precipitation, wind speed and humidity were prepared as ASCII format files. Considering the scale of the study area and the availability of measurements, these data were treated as homogenous for the entire area of the Qixing Farm.

3.1.2 Soil input data

A raster map of soil type data for the study area with a scale of 1: 1,000,000 was provided by the Chinese Academy of Agricultural Sciences (CAAS, www.caas.cn) in 2012. This dataset was produced based on the data which were collected in the second national soil survey of China in the 1980s. The soil data required as model input data were prepared as files in raster format. Nine raster datasets were prepared to represent the nine required soil parameters including soil organic carbon (SOC, kg C/kg soil), soil pH, bulk density (BD, g/cm³), soil porosity (0-1), soil texture (0-1), clay content (0-1), field capacity (FC, water-filled porosity at soil field capacity, 0-1), wilting point (WP, water-filled porosity at soil wilting point, 0-1) and saturated hydraulic conductivity (HC, m/hr).

The soil organic matter (SOM) and soil pH were measured in 2007 and 2008 by the local research center. In total, 1156 points evenly distributed over the Qixing Farm area were collected. Raster datasets of the SOC and soil pH were interpolated based on an ordinary kriging algorithm using the measured point data as input data. The ratio of SOC to SOM is assumed to be 0.58 (PRIBYL 2010). Raster datasets of BD and soil porosity were calculated from the SOC raster data according to eq. 1 (LI et al. 1992) and eq. 2 (BRIMHALL & DIETRICH 1987) respectively.

$$BD = \frac{k_1 k_2}{\frac{x}{100} k_2 + \left(1.0 - \frac{x}{100}\right) k_1} \tag{1}$$

$$Porosity = 1 - \frac{BD}{\rho_{particle}} \tag{2}$$

In equation (1), $k_1 = 0.14$, $k_2 = 1.6$, x stands for SOM (%). In eq. 2, $\rho_{particle}$ is the particle density, assumed to be 2.65 g/cm³.

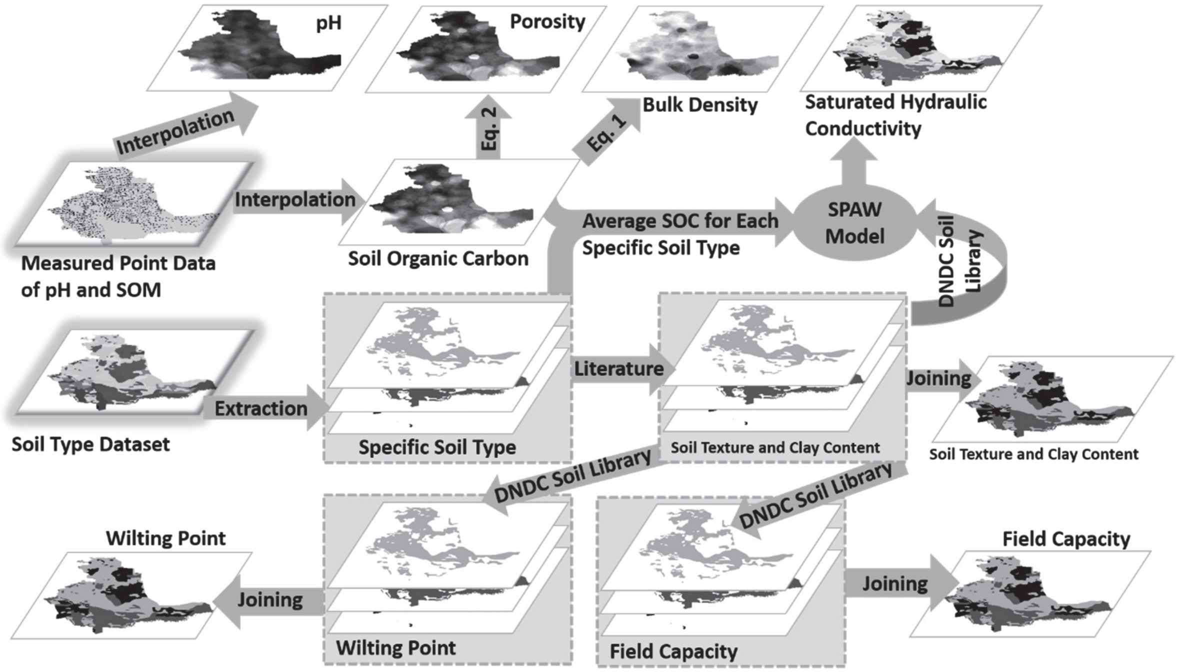

Fig. 1: Workflow of Deriving Raster Input Datasets of Soil Data.

Based on the soil type map, areas of specific soils (e.g. gleyed albic soil, meadow albic soil) were first derived. Raster datasets of soil texture and clay content were then prepared according to the published literature for these specific soils in the SJP (LIU et al. 2012, ZHANG & ZHANG 1988, WANG et al. 2011, WANG et al. 2002, MA et al. 2004, ZHANG 1981, HUO & LIU 1985). Raster datasets of FC, WP and HC for the specific soils were generated according to the DNDC soil library.

The SPAW (Soil-Plant-Air-Water) model (SAXTON & RAWLS 2006) was used to estimate HC based on clay content and SOC. Detailed procedures are shown in Fig. 1. All raster datasets were prepared with a raster cell size of 100 m × 100 m and were snapped to one reference raster (the soil type map).

3.1.3 Agricultural management data

In paddy rice fields, the flooding regime, residue management and application of nitrogen fertilizer are three major activities affecting rice productivity (ZHANG et al. 2011). In this study, management data regarding tillage, transplanting of the seedlings, nitrogen fertilizer topdressing, irrigation and harvest, were recorded for the growing season in 2009.

3.1.4 Field measurement data

Field measurements of agronomic data (e.g. leaf biomass, stem biomass, panicle weight, yield) for model calibration were collected at several dates during the growing season in 2009. Eleven sample sites in seven farmers' fields were selected. The measured agronomic data were used to calibrate crop parameters (e.g. maximum biomass production, biomass fraction of leaf, stem, grain) for the model. Detailed information on the field measurement is given in ZHAO et al. (2015).

3.1.5 Rice cultivation area map

A rice cultivation area map with field block boundaries for the whole study area was provided by the Qixing Farm Modern Agricultural Research Center. ZHAO et al. (2015) improved the map accuracy by combining the GIS vector file and multi-temporal high resolution satellite images.

3.2 Model improvement

In this study, the site-specific mode of the DNDC model was applied on the regional scale. To adapt the site-specific mode by running the model for each pixel of the interpolated input raster data automatically, additional scripts for assimilating the input raster data and generating output raster files were needed. These scripts were developed using Esri ArcGIS 10.1 and the scripting language Python version 2.7 and use the batch mode of the DNDC model.

To assimilate the model input data in the raster format, a script was developed to create "single-run" input files in the ".dnd" file format for each pixel of the raster datasets. These "single-run" input files were identified by the coordinate of the raster pixels. To minimize processing time, identical input files were only created once for all pixels having the same input parameters. To generate the output raster map, a second script was developed using the information stored in the first script to loop through all of the output files of DNDC's batch mode. For each requested output parameter such as crop carbon, nitrous oxide flux and methane emission, a raster was generated by assigning the required output parameters of the "single-run" files to the corresponding pixel coordinates.

4. Results

Modelled rice yield was analyzed on the regional scale for the Qixing Farm. The site-specific mode of the DNDC model was successfully applied for the raster cells, each with an area of 100 m × 100 m (Fig. 2, left). The spatial variability of rice yield within the field blocks is well detected. An average yield for each rice field block of the Qixing Farm was calculated using the rice cultivation area map and the tool "zonal analysis" in ArcGIS 10.1 (Fig. 2, right). The spatial variability of rice yield within the farm area is clearly shown.

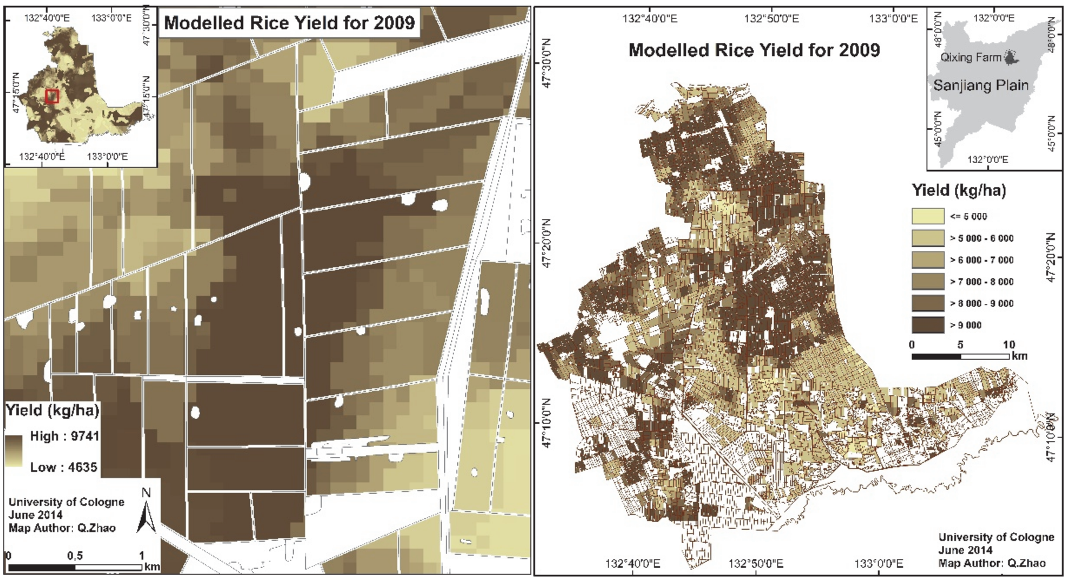

Fig. 2: Rice Yield Simulated by the DNDC Model for the Entire Qixing Farm on Pixel (left) and on Rice Field Block (right) Scale.

5. Discussion

Approximations of the spatial variability of crops provide basic information for precision agriculture management (MULLA 2012, ZHANG et al. 2002). In this study, the regional model input data were prepared as raster datasets with a pixel size of 100 m × 100 m to capture the spatial variability and therefore enable the analysis of rice production on field block scale. Although the pixel resolution of the input raster data can be infinitely increased, the accuracy of the final results in spatial variability depend on the (spatial) data quality of the original model inputs. Model execution time is another considerable factor in the implementation of the proposed method in a regional study. It is important to make a proper decision of the raster resolution by considering study aims, data quality, the size of the study area and available computation capability.
To evaluate the model results and improve the model accuracy, more work is needed including model validation, sensitivity tests, and analysis of different scenarios.

6. Conclusion

This study applied the site-specific mode of the DNDC model on a regional scale (120,000 ha) by defining specific model input data for each raster cell with an area of 100 m × 100 m. In addition, to improve the model capability, external scripts were developed which efficiently enabled the application of the site-specific mode on the regional scale by assimilating the raster input data automatically. The high spatial resolution of the model input data improved the model capability of representing the spatial variability of the modelled rice yield over the entire Qixing Farm.

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