Dynamic drought risk assessment using crop model and remote sensing techniques

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Abstract. Drought risk assessment is of great significance to reduce the loss of agricultural drought and ensure food security. The normally drought risk assessment method is to evaluate its exposure to the hazard and the vulnerability to extended periods of water shortage for a specific region, which is a static evaluation method. The Dynamic Drought Risk Assessment (DDRA) is to estimate the drought risk according to the crop growth and water stress conditions in real time. In this study, a DDRA method using crop model and remote sensing techniques was proposed. The crop model we employed is DeNitrification and DeComposition (DNDC) model. The drought risk was quantified by the yield losses predicted by the crop model in a scenario-based method. The crop model was re-calibrated to improve the performance by the Leaf Area Index (LAI) retrieved from MODerate Resolution Imaging Spectroradiometer (MODIS) data. And the in-situ station-based crop model was extended to assess the regional drought risk by integrating crop planted mapping. The crop planted area was extracted with extended CPPI method from MODIS data. This study was implemented and validated on maize crop in Liaoning province, China.

1. Introduction
Drought is a common occurrence natural disaster, which directly and primarily affects agriculture production. The Drought Risk Assessment (DRA) of agricultural has important significance for ensuring food security. Generally, DRA of a given region is to evaluate its exposure to the hazard and the vulnerability to extended periods of water shortage. This kind of analysis is to estimate the static risk of the region according to the characteristics of locality, normally it is an annual risk.

However, due to the slow occurrence/slow-onset characteristic of droughts (Wilhite, 1991), it is difficult to detect the emergence of droughts, monitor the situation, assess the impact and evaluate the risk. Specifically, the impacts on agriculture will be very different if the drought occurs during crop growth periods (Kulshreshta, 1989). Therefore, it is necessary to estimate the drought risk taking into account of the crop growth process and water stress conditions real-time.
There are a large number of studies on DRA (Wilhite, 2007; Zhou, 2010), but most of these studies are concerned with static DRA (Gong, 2010; Wilhite, 2000; Wu, 2004). Kumar (Kumar, 2007) indicated that crop yield is a comprehensive result of drought stress, so it can be used to quantify drought risk. Wu (Wu, 2004) suggested that the yield losses under drought stress can be used to measure the drought severities. These studies strongly support our method of using the crop model to assess the drought risk which described in this paper. Some similar ideas, such as Jia and Wang (Jia, 2012) using EPIC model to evaluate the maize drought risk of China, Yu and Li (Yu, 2014) using DNDC model to analyse the impact of drought. However, these studies mainly focus on the crop simulation process, but not the drought risk assessment.

In this paper, we propose to use crop model and remote sensing techniques for assessing drought risk dynamically. The main contributions of this paper focus on: 1) a Dynamic Drought Risk Assessment (DDRA) method based on crop model was put forward; 2) the remote sensing technique was used to help to promote the performance of the DNDC model and mapping the crop planted area.

2. Materials and Methodology

2.1 Framework of DDRA

The DDRA method we proposed mainly includes the crop modelling and remote sensing techniques. The crop model dynamically simulates the crop growth process and predicts the crop yield with a scenario based method. The remote sensing techniques will play two roles in the framework, which on the one hand is to retrieve the Leaf Area Index (LAI) to calibrate the crop model, and on the other hand is to extract the crop planting area. And the dynamic drought risk is quantitatively assessed with the predicted yield losses.

Figure 1. DDRA framework using crop model and remote sensing techniques.

The DDRA includes two procedures: a) model calibration & validation, and b) drought risk assessment. First of all, the model parameters were re-calibrated with remote sensing techniques, in which the model was revised partially according to the LAIs retrieved from remotely sensed images. After the development and validation of the model, it was implemented to predict the final crop yields dynamically. As the future climate conditions are unknown, we used a scenario-based method to make the assessment dynamically. It is significant to know how many area planted to assess the regional drought risk, which the annual crop planting area was extracted with a remote sensing techniques.

By this hybrid method combined of crop model and remote sensing techniques, the performance of the simulation was significantly improved, the in situ assessment was successfully extended spatially, and the drought risk can be assessed dynamically by the daily rolling simulation process.

2.2 Study Area and Data Description

The study area is Liaoning Province, located in northeast of China. It has 14 prefecture cities, 19 districts and 81 counties with agriculture planting. The annual precipitation ranges from 600 to 1100 mm, and the average annual temperature ranges from 7 to 11 °C. It is a drought prone area, especially
The severe droughts hit the northwest of the region more frequently. In recent years, more than 70% of the total farmland was maize of rain fed cultivated, which is out of the effect of irrigation during the analysis process of drought issue.

The data we utilized in the study mainly include meteorological data and remotely sensed images. The meteorological data consists of 820 rainfall stations and 27 meteorological stations with observations of temperature, precipitation, etc. from 1995-2009. The Thiessen polygon method was employed to partition the meteorological stations into separate zones, such that the rainfall stations in the identical zone had the corresponding temperature. The MODIS products of MOD15A2 (LAI) to and MOD13A1 (vegetation index) were used to calibrate the model and extract crop planted area, respectively.

2.3 Crop Model and Model Calibration

2.3.1 DNDC Model: The crop model we adopted is DNDC (DeNitrification-DeComposition) model (Li, 1992). It was widely applied in crop simulation and yield prediction (Han, 2014; Nyckowiak, 2013). The performance of the model has been verified for field and regional scales all over the world (Zhang, 2002). The model input consists of meteorological data, soil properties, land use and cultivation management, etc. The meteorological observations are the driven factors for the model running. Most of the parameters are available by measuring and surveying, while some need to be calibrated by the historical data to promote the performance of the model.

2.3.2 Model Calibration: The primary principle of model calibration is to make the simulated values as closed as possible to the observed ones. It is better to use multiple variables to perform the model calibration. In the study, we calibrated the model by variables of yield and Leaf Area Index (LAI), successively. First of all, the historical yields data were used to tune the parameters in a coarse process. And then, the remotely sensed retrieved LAI data were employed to make a fine calibration. As the yield-based calibration could not provide the ‘monitoring’ of the crop growth procedure, and a small number of samples (one record each year) are available for calibration. Thus, the LAI retrieved from remotely sensed images were used to re-calibrate the model. Many studies indicated that MODIS-LAI product is generally underestimated (Fensholt, 2004; Tian, 2002). The relationship between the MODIS-LAI and the ground truth vary with the crop and the season. It is proved that the MODIS-LAI is about 33%~53% under the synchronous ground measured LAI value (Yang, 2010). Here, we modify the MODIS-LAI by multiply a constant k, and given k equal to 1.5.

2.4 Crop Planted Mapping from Remote Sensing Images

An alternative remote sensing techniques for crop planted mapping could not only provide the result fast and cost saving, but also demonstrate the spatial distribution of crop planted. Based on the crop planted map, the site-based model could be extended to the regional one. A number of previous studies have attempted to map cropping planted area using remote sensing techniques in China (Li, 2003; Xiao, 2006). By now, the primary technique is the phenology-based remote sensing technique. However, the main challenge is to identify crop phenological cycles from time series of satellite-derived vegetation indices, such as the Enhanced Vegetation Index (EVI) or Normalized Difference Vegetation Index (NDVI) (Ganguly, 2010; Zhang, 2003). Here, we adopted a novel method to map the maize planted area, which was proposed by Pan and Li (Pan, 2012) and Li and Friedl (Li, 2014). Basically, it set up a Crop Proportion Phenology Index (CPPI) to quantitative analyse the relationship between the MODIS vegetation index (VI) time series and winter wheat crop area, and a time series mapping crop cycles in China was raised based on MODIS-EVI data.

Here, we implemented the maize phenology analysis from time series of MODIS-EVI data, and identified the planted area by CPPI specifically for maize. A series of 8-day MODIS product from 2000 to 2010 were used to mapping the crop planted area, and the Landsat TM images were sampled as ground-truth.

2.5 Drought Risk Assessment
2.5.1 Scenarios Analysis: Scenarios analysis ensure the accomplishment of the yield prediction. Each time to predict crop yield is a full simulation from sowing to harvesting. Based on the current time point, in the past time, the meteorological observations for the model input are available, however, in the future, the weather conditions are unknown. The scenarios are the assumption for future unknown weather conditions from now on to the harvest time. In this study, a series of scenarios were required to represent different drought conditions. Here, we specified 8 scenarios: 1) no effective rainfall in 5, 10, 20, 30 and 50 days, and without water stress afterwards, noted as S5, S10, S20, S30 and S50, respectively; 2) 3 typical years represent the wet, medium, and dry years, noted as SW, SM, and SD, respectively; 3) without water stress from now on to the harvest time, noted as S0.

2.5.2 Yield losses: The drought risk was quantitatively estimated by simulated yield losses. It is regarded that the simulated yield losses is entirely caused by drought disaster. Just because in the simulation process, the crop model integrated all the impact factors of drought intrinsically, and the ultimate yield losses completely come from water stresses. However, the main challenge is determine the normal yield. The normal yield we defined here is the potential maximum yield that the crop grow without any stress (such as water, temperature, fertilizer, etc.) during the whole growing season. Thus, the normal yield is completed determined by the crop physiological characteristics and the soil properties. Therefore, we simulated the normal yields by running the model under the condition of no stress preliminarily. Then the yield losses was directly obtained as the portion that the predicted yield less than the normal yield.

2.5.3 Drought Risk Classification: The drought risk classification carries out the grades of the drought risk severities according to the quantitative yield losses. Here, we categorized the drought risk by the yield losses rate instead of the amount. The drought risk is divided into 4 levels, which are I, II, III and IV with the yield losses rate of less than 10%, range from 10% to 25%, range from 25% to 35% and more than 35%, respectively.

3. Results

3.1 Model Validation

We used the parameters calibrated by data from 1995 to 2004 to simulate the yields for each county from 2005-2009. The result shows that the model estimated yield corresponded well with the reported yield from statistical yearbook (Figure 2). And then the provincial level yield can be obtained straightforward from the county level yield by multiplying the crop planted area retrieved from remotely sensed data. The provincial level yields estimation is evaluated with RMSE of 237.7 kg/ha, and R² of 0.77.

Figure 2. The comparison of the simulated yields and the historical reported yields in 2005-2009

Figure 3. Maize planted mapping of Liaoning Province in 2006
3.2 Maize Planted Mapping
A series of crop planted area in 2005-2009 was mapped using the remote sensing technique. Due to the stability of the planting structure, the annual crop sowing area would not have a great change. Therefore, here, we only present the maize planted map in 2006 (Figure 3). It can be seen that the major maize planted regions are in the north of the province, including Shenyang, Tieling, Fuxin and Jinzhou, etc., which is in agreement with the reported results from statistical yearbook (Table 2). Statistically, the planted area of each prefecture was retrieved from the map, and compared with the statistical yearbook data (Table 2). The Mean Absolute Percentage Error (MAPE) is 21.0%, 16.3%, 14.2%, 14.3% and 13.8% from 2005 to 2009, respectively.

Table 2. The maize planted area from remotely sensed images (column “RS”) and the records from statistical yearbook (column “SY”) for each prefectures in Liaoning Province. (unit: 10^3 ha)

| Prefecture | 2005  | 2006  | 2007  | 2008  | 2009  |
|------------|-------|-------|-------|-------|-------|
| Shenyang   | 337.0 | 346.8 | 305.7 | 337.5 | 304.8 |
| Dalian     | 180.6 | 191.1 | 185.6 | 197.5 | 182.9 |
| Anshan     | 152.4 | 161.7 | 160.6 | 172.3 | 160.1 |
| Fushun     | 59.1  | 43.7  | 69.2  | 51.2  | 68.2  |
| Benxi      | 35.0  | 6.5   | 35.3  | 24.6  | 35.1  |
| Dandong    | 95.2  | 64.2  | 99.4  | 78.5  | 98    |
| Jinzhou    | 265.3 | 307.5 | 281.8 | 290.6 | 271.8 |
| Yingkou    | 41.9  | 47.5  | 46    | 48.2  | 46.6  |
| Fuxin      | 200.5 | 212.7 | 215.9 | 231.1 | 193.7 |
| Liaooyang  | 78.6  | 68.9  | 79.1  | 66.3  | 78.7  |
| Panjin     | 13.5  | 20.9  | 13    | 18.8  | 13.6  |
| Tieling    | 302.1 | 341.6 | 303.2 | 356.8 | 276   |
| Chaoyang   | 191.0 | 216.7 | 216.5 | 240.4 | 215.3 |
| Huludao    | 124.6 | 145.2 | 126.1 | 151.2 | 145.2 |

3.3 Case study in Liaoning Province
Based on the crop model simulation, scenarios analysis and crop planted mapping techniques described above, the DDRA can be implemented day by day. Here, only the cases of June 1, 2009 (Figure 4) and July 1, 2009 (Figure 5) in Liaoning Province, China were demonstrated, respectively.
The results show that the drought risk grades increased if no effective rainfall days prolonged. And no effective rainfall within 10 days (S0, S5 and S10) will not lead to a substantial increase in yield losses, but more than 30 days no effective rainfall (S30) will result in sharp yield losses. This is because the soil moisture could meet the crop growth in a limited time, which basically in the scope of one month. According to the comparative analysis of Figure 4 and Figure 5, the drought risk had increased from June 1 to July 1. This is proved that the amount of rainfall in Liaoning is seriously low, which only 18% of average annual value. Due to the previous drought stress, even the scenario of wet year (Sw) and without water stress hereafter (S0) were of significant risk yet. Spatially, the drought risk in the northwest region is generally higher than in other regions, which is coincident with the reality.

The case study shows the complete process of the method and proved its reasonability. This method can be implemented in a real-time to dynamically assess the drought risk. The result is very helpful for drought mitigation.

4. Conclusion
This study proposed a dynamic drought risk assessment method using crop model and remote sensing techniques. We employed the DNDC model to simulate the crop growth process and predict the yield. After calibrating the crop model by series of historical yield records, we then re-calibrated the model by LAI retrieved from MODIS data during crop growing. A scenario-based method was used to solve the problem of unknown future climate conditions. Then the drought risk was quantified by the yield losses. And the future drought risk was evaluated under the assumed scenarios. However, the in situ drought risk assessment could be extended to regional analysis by integrating the crop planted mapping with a remote sensing method.
The case study for maize in Liaoning Province, China shows that the DDRA method was validated and applicable. This method is of great significance for drought mitigation in practical application. The manager could make an appropriate drought relief measurement according to DDRA results, including the current water stress of the crop and the future crop yields, etc.

However, there are a lot of sophisticated analysis in these method. In the future, we will continuously improve the model performance, integrate the weather forecasting result in the scenarios, promote the crop mapping accuracy, and so on.

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