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Estimating seasonal fragrant rice production in Thailand: A review article

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Abstract The article is reviewed the current and existing methods of fragrant rice crop yield and production forecasts in Thailand and their potential application for seasonal prediction. While several government agencies have carried out the forecast task, however, the further research is needed in order to minimize risk and maximize efficiency of agricultural resources. Incorporation of emerging methods could lead to a new strategy to forecast yields and production as well as to provide timely and reliable forecasts, by adopting integrated agro-informatic tools. The manual crop cutting, end-of-season farmer surveys, remote sensing, spatial databases and decision support system tools and simulation models were reviewed. We concluded that the spatial databases and climate and crop simulation models provided the opportunities to establish an inclusive and integrated platform for farmers, government agencies and private firms to participate in the important task of seasonal forecasting for fragrant rice production systems in Thailand.

Keywords: KDML105 rice variety, Agro-informatics, agricultural resource databases, CSM-CERES-Rice model, ORYZA2000 model

Introduction

Timely and accurate crop yield estimation is an essential management tool to regulate the common agricultural markets (Supit, 1997). The estimated results are used by multiple stakeholders in several ways to improve crop production outcomes by minimizing inputs and maximizing efficiency in sustainable agricultural practice and precision farming (Challinor, 2009; Zhang *et al*., 2002). An estimation of seasonal crop yield is necessary for agricultural information systems, and tools for this have been developed for cotton in the southeastern United States (Baigorria *et al*., 2010; Mauget *et al*., 2013), several

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crops in Europe (Cantelaube and Terres, 2005), and rice in the Philippines (Koide *et al*., 2013). At a plot level of crop production, using process-oriented models for seasonal yield forecasts may help to optimize crop management decisions such as site-specific chemical fertilizer application rates (Ratjen and Kage, 2015).

The purpose of this review is to provide a summary of crop and rice yield and production forecasts using various methods and to discuss methods focused specifically on fragrant rice (also known as jasmine rice) in Thailand, using simulation models and spatial databases currently and routinely operated by various agencies in the Ministry of Agriculture and Cooperatives and the Ministry of Science and Technology in Thailand.

A photoperiod-sensitive rice production ecosystem in Thailand

In 2015, Thailand had a total land area of approximately 51 million hectares, allocated as non-agricultural lands (11 million hectares), forest lands (16 million hectares) and agricultural lands (24 million hectares). Of the agricultural lands, approximately 9.3 million hectares were allocated for rice paddies during the main rice-growing season between May and December (OAE, 2016). There were two major photoperiod-sensitive rice varieties: RD6 (glutinous rice) occupied an area of 1.7 million hectares and KDML 105 variety, (non-glutinous fragrant rice) covered an area of 4.0 million hectares (DOAE, 2017).

A rice production ecosystem is a major contributor to food security and generates cash income for farmers' households and the country under various agroecosystems (AE). The Thailand Rice Department has defined seven rice production ecosystems (Figure 1), based on provincial administrative boundaries in Thailand. A successful rice paddy field depends on numerous abiotic and biotic factors, such as soil physical and chemical conditions, solar radiation, air temperature, rainfall and crop management (e.g., rice variety, planting date, fertilizer application and water management). In addition, spatial soil properties and weather variability cause spatial and temporal rice yield variability. As a result, a system for forecasting seasonal photoperiod-sensitive rice yields is an important tool for optimizing rice production ecosystems.

In 2015, Thailand was one of the principal rice (*Oryza sativa* L.) exporting countries and earned foreign income of more than 150 billion Baht with around 30 percent of the total income from fragrant rice (TREA, 2016). During the main rice-growing season in 2015, the country allocated some 9.3 million hectares or around 39% of the total agricultural land area of the whole Kingdom to paddy rice production (OAE, 2016).

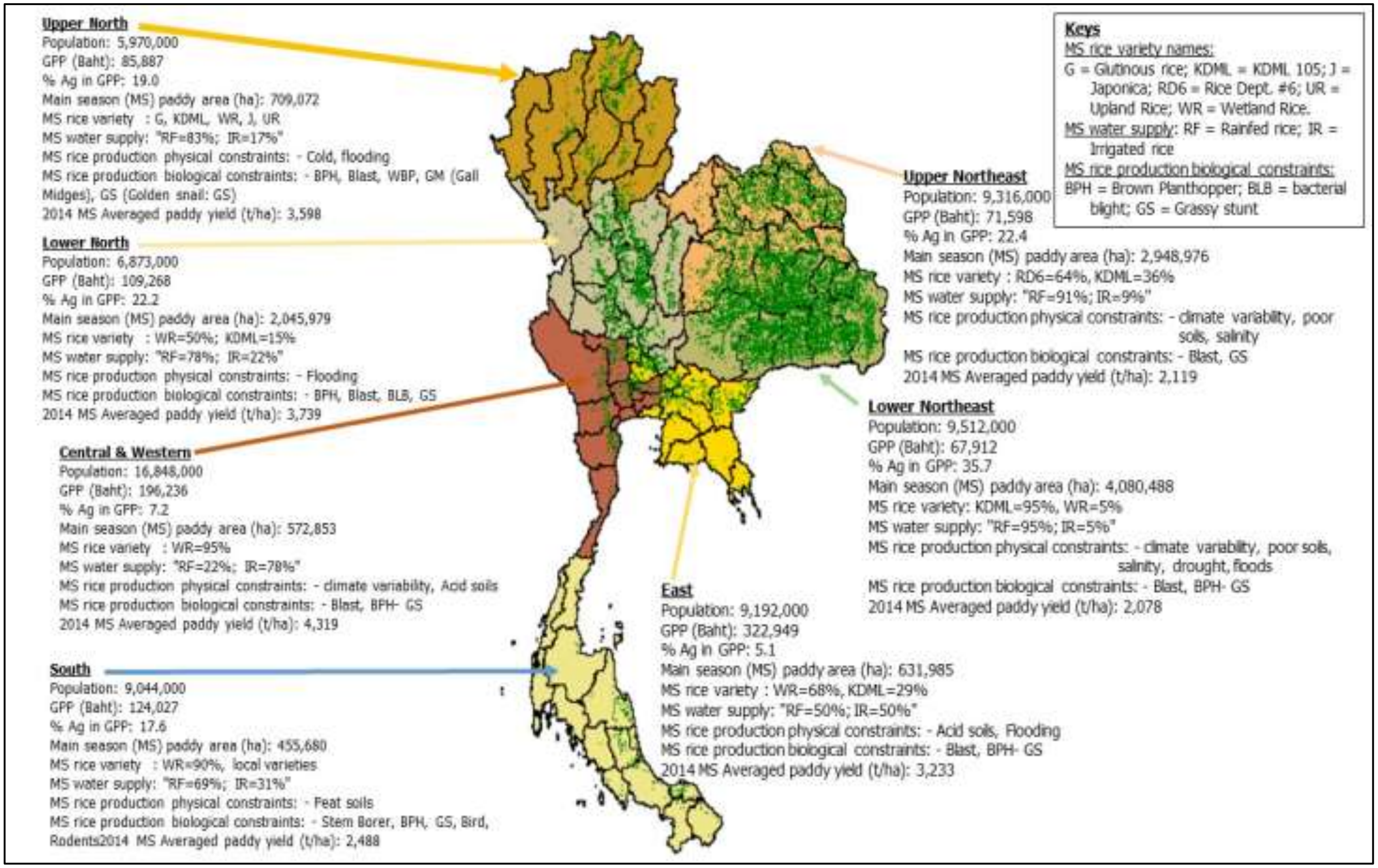

Figure 1. Seven rice production ecosystems in Thailand. Source: Thailand Rice Department, 2018

Thai Hom Mali rice is the principal fragrant rice category, consisting of two varieties, namely KDML 105 and RD15 (NBACFS, 2017). According to the farmers' registration system used during the 2015/16 main rice-growing season by DOAE, the areas planted with rice varieties RD15, KDML 105 and other rice varieties are 0.3, 4.0 and 5.0 million hectares or 3%, 43% and 54% of the total rice-planted areas, respectively (DOAE, 2017).

Current rice yield and production forecast methods

The Office of Agricultural Economics (OAE) is the only agency under the Thai government's Ministry of Agriculture and Cooperatives responsible for announcing and providing the official annual data sets that cover all major economic crops including rice. In each main rice growing season, OAE releases forecasts and reports at a district level on rice planted areas, averaged paddy yield and total rice production. The agency releases the report when rice planted areas have reached approximately 40% of the total areas and when rice is approaching the harvesting period using a statistical approach and crop cutting method (OAE, 2014, 2016). In addition, the Geo-Informatics and Space Technology Development Agency (GISTDA) has been producing rice planted areas digital maps with estimates of rice yield at fortnightly intervals since 2013. The digital maps and related information are then published and distributed in shapefile format on GISTDA's website (GISTDA, 2018). To estimate the paddy rice production of a given polygon in the shapefile, the average fortnightly paddy rice yield of a fixed rice-cropping duration of 120 days after planting was multiplied by the area of planted rice determined from satellite images. In summary, the methods implemented by OAE and GISTDA do not account for the dynamics of weather and soil conditions or for rice varieties and rice management practices in various rice ecosystems. Consequently, there is a need for an integrated agro-informatics system to support the realistic estimation of paddy rice yield and production, which allows the users to incorporate weather, soil, rice variety and management practices data sets. Furthermore, the forecasts could be issued three to four months prior to the harvest period using process-oriented crop simulation models and spatial and attribute data sets, including seasonal weather forecasts, soil groups, and rice-planted areas, so that better planning can occur.

Emerging crop yield and production forecast methods

Crop yield and production forecasts for seasonal growing periods are of interest for farmers, traders and policy makers. Various crop yield forecast methods have been developed for quantifying production of agricultural systems at plot, region or national levels. Sapkota *et al*. (2016) compared various methods of crop production estimation with their cost-effectiveness, scale and accuracy (Table 1). Brief descriptions of each method follow.

Crop cutting

In the 1950s, a method of forecasting crop yields by randomly sampling frames about 1 meter by 1 meter square within a field was initially developed in India. The crop cutting method was subsequently adopted as a standard recommended by the Food and Agriculture Organization of the United Nations (FAO) to estimate and forecast crop production at the harvesting period for various crops (FAO, 1982; Fermont and Benson, 2011; Sapkota *et al*., 2016). In this method, crop yields in one or more frames were measured and total crop yield per unit area was calculated as the total production divided by the total plot area. Sapkota *et al*. (2016) suggested that the size of the sampling frames should be at least one-meter square to obtain reasonable and acceptable crop yield and production forecasts. In a field with variable crop performance, it was advisable to use even larger sampling frames or increase the number of sampling frames for crop yield estimation, but it was a time and labor-intensive method.

Remote sensing

The remote sensing method is based on the principle of differing spectral reflectance of surfaces, i.e., crops and other land surfaces. The sensors on board a satellite were used to collect the reflected electromagnetic radiation signals from the surfaces, which subsequently are used to calculate the Normalized Difference Vegetable Index (NDVI). According to Johnson *et al*. (2016), the Moderate Resolution Imaging Spectroradiometer (MODIS)-NDVI was the most effective NDVI value to forecast crop yields by Multiple Linear Regression. However, the NDVI tracked only the vegetative development, but could not determine crop grain yield (Mkhabela *et al*., 2005).

In Thailand, GISTDA, which is under the Ministry of Science and Technology, is the only Thai Government agency in charge of providing fortnightly data on planted-rice areas. The data has been derived from the MODIS satellite observations since January 2014 and is provided in shapefile format. However, these shapefiles currently do not include seasonal rice yield forecasts by integrating a crop simulation model and seasonal climate forecasts (GISTDA, 2018).

Rice Simulation Models

Process-based crop simulation models, including the CSM-CERES-Rice model (Ritchie *et al*., 1987; Singh *et al*., 1989), were designed to simulate rice developmental stages and growth on a daily time scale. Moreover, these models can respond to and capture different environment factors, such as planting date, rice variety, water management, nitrogen chemical fertilizer management and crop residue (Basso *et al*., 2016; Hoogenboom, 2000; Hoogenboom *et al*., 2017; Jones *et al*., 2003; Tsuji *et al*., 1998). Jintrawet and Kaeomuangmoon (2016) developed a prototype of an integrated agro-informatics system tool called the DSS-SRY4cast tool for users to forecast paddy rice yield four to six months in advance for six different planting dates during the 2016 main rice-growing season in Thailand. However, they did not specifically focus on KDML 105 at the district level.

The process-based crop and rice simulation models were used to simulate crop growth, developmental stages, and yields that are influenced by soil profile characteristics, daily weather data, crop variety and crop management on a daily time step from planting until harvesting times (Hoogenboom, 2000). It was found that these crop simulation models could be accurate and precise when they were calibrated and evaluated with field observations from various sites under real crop production situations (Hunt and Boote, 1998). However, the accuracy of forecasted crop yields can be improved when there are outbreaks of pests or plant diseases by linking pest effects to the crop model (Teng *et al*., 1998).

ORYZA2000 simulation model: The International Rice Research Institute (IRRI) and Wageningen University and Research Centre have developed the ORYZA2000 model to simulate growth and developmental stages of lowland rice in situations with variations of potential production, such as water limits and nitrogen limits (Bouman *et al*., 2001). The ORYZA2000 model had four phenological phases: the juvenile phase, the photoperiod-sensitive phase, the panicle development phase and the grain-filling phase (Arora, 2006). The model followed a daily calculation scheme for the rate of dry matter production of various rice organs and for the rate of phenological development. By integrating these rates over time, dry matter production and developmental stages were simulated throughout the growing season (Bouman and van Laar, 2006). The ORYZA2000 model was not designed and tested for photoperiod-sensitive rice varieties. The newest version has been renamed "ORYZA version 3 (v3)" (Li *et al*., 2017). According to Amiri *et al*. (2014), the comparison of the performance of three rice dynamic models (CSM-CERES-Rice, AquaCrop, and ORYZA2000) in simulating biological processes and grain yields of rice showed that the CERES-Rice model was the most accurate in approximating grain yields under different irrigation intervals and nitrogen applications.

Table 1. Crop yield forecast methods with description of cost effectiveness, intended scale and precision

Crop yield forecast methods	Cost effectiveness	Scale	Precision in forecast, error and bias
Crop cut	Time and labor intensive	Field, farm and sometimes landscape level	Tendency to overestimate
Farmer's estimate	Cheap and quick method that saves time and money	Farm to landscape	Fairly accurate estimation but needs adequate supervision. Subjective. Sometimes farmers deliberately overestimate or underestimate.
Crop modeling	Cost effective	Plot to Landscape	Less error and bias if adequately parameterized and calibrated. Does not include induced improvements in agricultural technology
Remote sensing	Cost effective	Landscape	Chances of error in cases where different crops have same signature

Source: Sapkota *et al*. (2016)

CSM-CERES-Rice simulation model: The Decision Support System for Agrotechnology Transfer (DSSAT) was designed to accommodate 16 simulation crop models (CSM) from the CROPGRO and CERES models and has primary modules for weather, soil, plant, soil-plant-atmosphere, and crop management (Jones *et al*., 2003). The CERES-Rice model, a model under the DSSAT package, was developed to simulate nine rice developmental stages, rice growth processes, and biomass partitioning of a rice crop on a daily basis according to climatic data, water and nitrogen balances and cultivar characteristics (Ritchie *et al*., 1998; Timsina and Humphreys, 2006). Bannayan *et al*. (2003) indicated that the CERES-Rice model has demonstrated reliability under different climate, soil, and management conditions. Chun *et al*. (2016) and Jintrawet and Chinvanno (2011) assessed the impacts of climate change on rice yields in Southeast Asia using the projected climate data from two climate change models. Using the CSM-CERES-Rice model together with climate change A2 and B2 scenarios as predicted by the PRECIS RCM, downscaled from the ECHAM4 GCM data set, they concluded that during 1980-2099, rice production in Thailand showed changes, with slight declines in main season rice yields before the 2040s and drastic decreases after this time. Similar rice yield decreases were found when output from the Conformal Cubic Atmospheric Model (CCAM) downscaled projections for the RCP4.5 and 8.5 scenarios (Katzfey *et al*., 2014; Katzfey *et al*., 2016) were used with the CSM-CERES-Rice model (Jintrawet *et al*., 2017).

The CSM-CERES-Rice model emphasizes the effects of crop management and the influence of weather conditions and soil properties on crop performance. The model was designed to assess rice yield as captured by rice varietal characteristics. The model was also used to decide on how best to implement soil water and nitrogen management for alternative production options and for various growing sites. Weather inputs include daily solar radiation, maximum and minimum temperatures and precipitation. Potential effects of extreme events, i.e., storm events, and high and low temperature are ignored, and no pest infestations are assumed. The influence of carbon dioxide (CO_2) on photosynthesis and transpiration has recently been added to assess the impact of increased CO_2 on rice yield under various climate change scenarios.

The CSM-CERES-Rice model version 4.7, within DSSAT v4.7, has daily outputs and requires four minimum data sets, namely weather, soil, rice genetic coefficients, and rice management practices throughout the growing season (Table 2).

Available spatial databases in Thailand

KDML105 rice-planted area maps

GISTDA released maps of areas planted with rice fortnightly and posted the data set on their website (Mitkalaya *et al*., 2013). These rice planted areas were processed from the MODIS surface reflectance 8-day L3 Global 250 m SIN Grid V005 or MOD09Q1 data set from 2013 to 2015 (Bridhikittti and Overcamp, 2012). To obtain the planted area for KDML105 rice, we linked the fortnightly rice-planted areas shapefile, released by GISTDA six times during the main growing season from June to August in 2013, 2014, and 2015, with the farmer registration database administered and operated by the DOAE. By linking data from these two sources, we created the KDML105 planted-area shapefiles data sets with administration codes for the 2013 to 2015 growing seasons for six planting dates for each growing season (Table 1). During the periods of these six planting dates, on average all 77 districts received about 180–300 mm of rain per month, which is sufficient to produce a reasonably good rice crop (Yoshida, 1981).

Table 2. Contents of minimum data sets for operation of the CSM-CERES-Rice model

Data set	Description
Required minimum data sets	
Weather	• Daily global solar radiation, maximum and minimum air temperatures, precipitation
Soil	• Classification using the local system and (to family level) the USDA-NRCS taxonomic system • Basic profile characteristics by soil layer: in situ water release curve characteristics (saturated drained upper limit, lower limit); bulk density, organic carbon; pH; root growth factor; drainage coefficient
Rice genetic coefficients	• Four phenological and four growth coefficients for each rice variety.
Crop Management	• Soil water, ammonium and nitrate concentration by soil layer • Cultivar name and type • Planting date, depth and method; row spacing and direction; plant population • Irrigation and water management, dates, methods and amounts or depths • Chemical fertilizer (inorganic) applications • Residue (organic fertilizer) applications (material, depth of incorporation, amount and nutrient concentrations).
Auxiliary data set	
Site	• Latitude and longitude, elevation; average annual temperature; average annual amplitude in temperature • Slope and aspect; major obstruction to the sun (e.g. nearby mountain); drainage (type, spacing and depth); surface stones (coverage and size)
Initiate conditions	• Previous crop, root, and nodule amounts; numbers and effectiveness of rhizobia (nodulating crop)

Source: Jones *et al*. (2003).

Seasonal weather forecasts in Thailand

Weather conditions have significant impacts on crop growth and developmental stages and have major impacts on pests and diseases, so crop yield variability is affected by year-to-year climatic variability (Hoogenboom, 2000). Accurate forecasts of weather 3–6 months in advance can potentially allow farmers and policy makers in various agricultural systems to make proper decisions to reduce unwanted impacts or take advantages of expected favorable climate and weather conditions (Jones *et al*., 2000).

Statistical seasonal weather forecast data sets, generated from the historic range of climate variations, can be applied to estimate current crop conditions or potential yields. During the beginning of the crop growing season these forecasts have ranges of predictions for variables such as temperature and rainfall rather than specific values due mainly to the incorporation of all historical climate variability, leading to a large range of possible outputs from the models. Dynamical seasonal climate models, such as the Weather Research and Forecasting (WRF) model, offer the opportunity to narrow this range, contingent on the models having adequate predictive skill (Brown *et al*., 2018). WRF is a widely used open-source model that allows the users to create different configurations tailored to the needs of each study. The WRF model is based on physical principles (Chotamonsak *et al*., 2011), and can provide probabilistic predictions of the seasonal mean climate. It also generates daily time series of the evolution of the weather and thus provides more detailed information on the weather statistics during the season. These daily time series can be used to drive applications models such as a crop model; however, some spatial downscaling of the data may be required. Grosz *et al*. (2015) applied and tested WRF with the DNDC model (DeNitrification DeComposition Model) for greenhouse gas flux simulation. Kioutsioukis *et al*. (2016) applied high resolution (2-kilometer grid) WRF ensemble forecasting data to irrigation.

Capa-Morocho *et al*. (2016) found that disaggregating seasonal climate forecasts into daily weather data and using it as input data for crop simulation models provided predictability for crop yield and production. The crop yield forecasts and irrigation requirements from the crop model could be considered as a production cost and were used to analyze likely gross margins to help farmers making a decision when the seasonal rainfall forecast was below normal.

Applications of weather forecast data sets to agricultural decision problems are, therefore, numerous and rely on the possibility of translating the meteorological content of the forecasts into agricultural terms. Users can gain economic benefits from weather information for short-term (tactical) decisions as well as long-term (strategic) decisions. In many areas of the world, access to seasonal weather forecasts is still limited, but efforts are being undertaken at various levels to improve on this situation (Calanca, 2014).

Decision support system tools in Thailand

Jintrawet (2009) developed the Crop Production Systems Decision Support System (CropDSS), which consists of the Spatial Database Management System (SDBMS), Model Base Management System (MBMS), analysis programs and map display functions (Figure 2). This tool facilitated linking of four minimum spatial databases, namely administrative boundary, crop planted areas, soil series boundary, and climate grid maps with four crop simulation models under the DSSAT package.

The CropDSS agro-informatics tool was used to simulate potential rice production options for Thailand under various climate change scenarios. Under the ECHAM4 SRES A2 scenario, predictions of rainfed rice production in the Chi and Moon River Basin in the northeast of Thailand show that rice yield will be increased at the rates of 15.5 and 11.1 percent compared to recent Chi and Moon rice yields, respectively, by the year 2099 (Buddhaboon and Jintrawet, 2009). When data from multiple high-resolution (10 km) downscaled simulations produced using the Conformal Cubic Atmospheric model (Katzfey *et al*., 2014; Katzfey *et al*., 2016) for two CMIP5 RCPs (lower 4.5 and high 8.5 greenhouse gas concentrations) were input into the CROPDSS agro-informatics tool, it was shown that most projections give a decrease in rice yields during 2006–2040 relative to the baseline (Jintrawet *et al*., 2017).

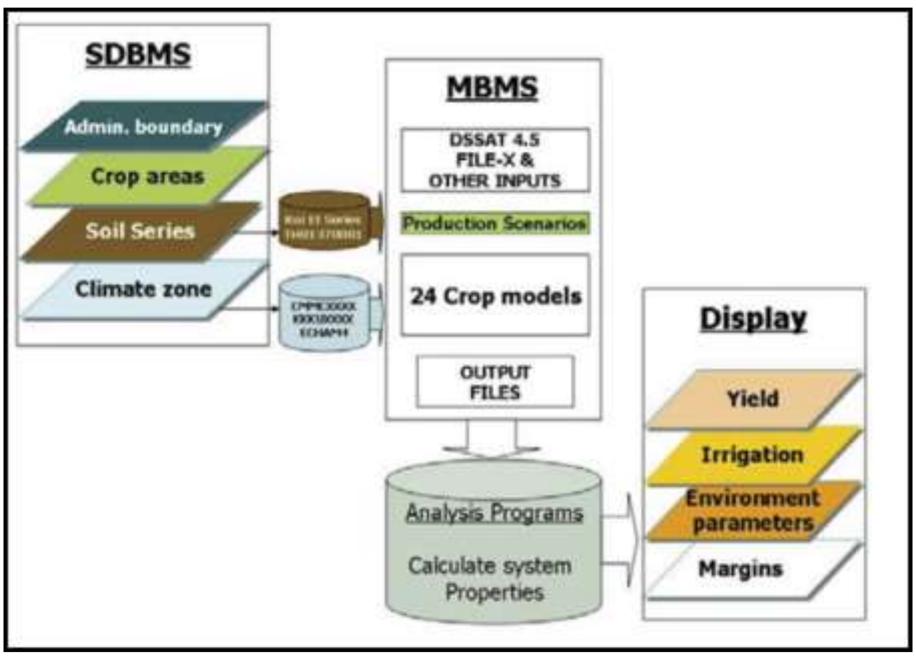

Figure 2. Overview of the components and modular structure of CropDSS interface, Source: Jintrawet (2009)

Jintrawet and Kaeomuangmoon (2016) have developed an agro-informatics prototype called the DSS-SRY4cast tool for users to produce rice yield forecasts 4-6 months in advance for six planting dates during the 2016 main rice-growing season in Thailand. However, there are no estimates of the environmental and economic risk of rice production scenarios in various parts of the country.

A reliable seasonal paddy rice yield forecast system requires as a minimum spatial data sets and attribute data sets, i.e., rice cropping management, rice planted area, soil group and seasonal weather forecast data sets, which are provided by various Thai agencies. The rice-planted areas data set is updated fortnightly and the seasonal weather forecast data set is updated monthly. Each data set is large and covers rice-planted areas throughout the country. SDBMS can help to store large data sets and connect to GIS software to create maps, conduct data analysis and produce visualizations of spatial data (Tragila *et al*., 2010; Van Den Eeckhaut and Hervás, 2012; Jäger, 2018).

Discussion

Non-glutinous fragrant rice variety KDML 105 covered an area of approximately 4.0 million hectares or 43% of annual total rice planted in Thailand (DOAE, 2017; OAE, 2014, 2016). Because rice is linked with food and income security of millions of small farm households, it is imperative and essential for the country to invest in the development and implementation of a reliable and accurate rice yield estimation tool (Supit, 1997).

The availability of climate and crop simulation models and spatial data sets in Thailand offer a unique opportunity for integrating data and information on the bio-physical properties of the major staple food crop in various rice ecosystems in Thailand, especially fragrant rice KDML 105 (OAE, 2014, 2016; Mitkalaya *et al*., 2013). Spatial data sets, together with geo-referenced maps and a dynamically downscaling climate model such as CCAM and WRF can be used for providing production forecasts and seasonal estimates of rice yield 3-4 months in advance using an integrated agro-informatic tool. The geo-referenced maps from GISTDA and attribute data sets from other agencies in Thailand could be linked with other field-level data sets (GISTDA, 2018).

Conclusion

We have reviewed various methods and approaches for estimating seasonal fragrant rice production in Thailand. Seasonal rice production techniques have advanced greatly over the last few decades and improved substantially in recent years. These improvements were due to better understanding of soil-plant-weather-management processes, advances in computing, improved simulation models, increased availability of data and higher standards enhance the ability to implement decision support systems. In conclusion, the real value of using simulation models and spatial data sets, combined as an integrated agro-informatic forecasting tool, as described in our review, is that it will help the farmers and policy makers to collaboratively utilize and optimize agricultural resources for sustainable fragrant rice production systems.

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