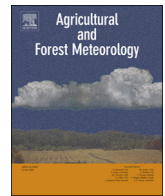




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## BESS-Rice: A remote sensing derived and biophysical process-based rice productivity simulation model

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### ABSTRACT

Conventional process-based crop simulation models and agro-land surface models require numerous forcing variables and input parameters. The regional application of these crop simulation models is complicated by factors concerning input data requirements and parameter uncertainty. In addition, the empirical remotely sensed regional scale crop yield estimation method does not enable growth process modeling. In this study, we developed a process-based rice yield estimation model by integrating an assimilate allocation module into the satellite remote sensing-derived and biophysical process-based Breathing Earth System Simulator (BESS). Normalized accumulated gross primary productivity ( $GPP_{norm-accu}$ ) was used as a scaler for growth development, and the relationships between  $GPP_{norm-accu}$  and dry matter partitioning coefficients were determined from the eddy covariance and biometric measurements at the Cheorwon Rice paddy KoFlux site. Over 95% of the variation in the dry matter allocation coefficients of rice grain could be explained by  $GPP_{norm-accu}$ . The dynamics of dry matter distribution among different rice components were simulated, and the annual grain yields were estimated. BESS-Rice simulated GPP and dry matter partitioning dynamics, and rice yields were evaluated against *in-situ* measurements at three paddy rice sites registered in KoFlux. The results showed that BESS-Rice performed well in terms of rice productivity estimation, with average root mean square error (RMSE) value of  $2.2 \text{ g C m}^{-2} \text{ d}^{-1}$  (29.5%) and bias of  $-0.5 \text{ g C m}^{-2} \text{ d}^{-1}$  (-7.1%) for daily GPP, and an average RMSE value of  $534.8 \text{ kg ha}^{-1}$  (7.7%) and bias of  $242.1 \text{ kg ha}^{-1}$  (3.5%) for the annual yield, respectively. BESS-Rice is much simpler than conventional crop models and this helps to reduce the uncertainty related to the forcing variables and input parameters and can result in improved regional yield estimation. The process-based mechanism of BESS-Rice also enables an agronomic diagnosis to be made and the potential impacts of climate change on rice productivity to be investigated.

### 1. Introduction

The challenges of food security and regional food inequalities will update over time due to the rapid increase in global food demand and aggravation of climate change (Tilman et al., 2011; Wheeler and Von Braun, 2013). Hence, there is an urgent need to accelerate food production and productivity. The sustainable intensification of crop production is therefore of great importance (Reddy, 2016). Successful crop productivity estimations are important for cultivation management and agricultural decision-making (Hochman et al., 2009; Kassie et al.,

2016). The estimation of accurate crop production also facilitates a better understanding of the way crop growth and production responses to environmental factors (Bregaglio et al., 2017; Guan et al., 2016; Tollenaar et al., 2017).

Process-based crop simulation models use quantitative descriptions of ecophysiological processes to simulate crop growth and development as influenced by environmental conditions and management practices (Hodson and White, 2010). Therefore process-based crop simulation models can be used to understand the mutual effects among crop genotypes, management, and the environment (Messina et al., 2009). These

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crop simulation models have also been widely used to investigate the potential impacts of climate change on agricultural productivity (Asseng et al., 2015; Rosenzweig et al., 2014) and to explore the management options under current growing situations (Hochman et al., 2009; Kassie et al., 2016). Moreover, agro-land surface model, which is a land surface model or dynamic vegetation model incorporated with a crop simulation model, is a useful tool for simulating the fluxes of heat, water, and gases in agricultural land (Masutomi et al., 2016a).

Conventional process-based crop simulation models and agro-land surface models, however, require numerous forcing variables, including genetic specific data, soil physicochemical characteristics, management practices, and agro-meteorological data; and input parameters, including soil-type specific, crop specific, simulation setting, and other coefficients. (Li et al., 2015; Masutomi et al., 2016a). The regional application of such models is complicated and hampered by factors concerning input data requirements and parameter uncertainty. Information regarding regional differences in crop management, cultivar distributions, and coefficients for parameterizing agro-environmental processes are usually unavailable (Folberth et al., 2016a). Previous studies have shown that the uncertainties of crop cultivars and management (Folberth et al., 2016a), soil characteristics (Folberth et al., 2016b; Varella et al., 2012), meteorological conditions (Li et al., 2015; Zhao et al., 2015), and parameters settings (Ramirez-Villegas et al., 2017; Tao et al., 2018) all influence the accuracy of crop production simulation. Relatively, regional agro-meteorological variables are available from the reanalysis datasets, which are derived from the systematic approach based on surface observations, models and data assimilation (Rienecker et al., 2011).

Remote sensing can provide temporally and spatially continuous information regarding crop biophysical variables and estimates of crop yield (Battude et al., 2016; Burke and Lobell, 2017; Lobell et al., 2015). The usefulness of remote sensing for interpreting the process of crop production and how it responds to environmental factors, however, is clearly inferior compared with the process-based crop simulation models. Recent studies have revealed that crop yield can be reliably estimated from the satellite-based crop gross primary productivity (GPP) (Guan et al., 2016; Xin et al., 2013; Yuan et al., 2016). Such estimations are based on the use of a crop-specific harvest index (HI) to convert net primary productivity (NPP) data to yield at the harvest time, which does not consider the process of yield formation. Yuan et al. (2016) simulated different types of crop yield based on the satellite-based light use efficiency model derived GPP estimations at 12 sites across Europe and North America, using HI and a constant carbon allocation coefficient and did not take into account temporal or spatial variations. The results showed that yield was underestimated by between 61% and 32% at several sites and overestimated from 34% to 55% at other sites in their study.

Integrating remote sensing information and process-based crop simulation models can maximize their advantages. Remote sensing can support crop modeling by monitoring vegetation status at regional scale, which would be very difficult to obtain otherwise (Dorigo et al., 2007). Process-based crop simulation models can dynamically simulate the carbon, nitrogen, and water balances at daily or hourly time-steps to estimate crop growth and development (Boote et al., 2013). Many studies improved the crop growth simulation and yield estimation using the data-model integration approaches (Casa et al., 2012; Huang et al., 2013; Jin et al., 2017; Zhang et al., 2016). Almost all these previous studies have used remote sensing-derived vegetation indices or biophysical and biochemical variables, e.g., leaf area index (LAI), biomass or leaf nitrogen accumulation, to improve the crop simulation processes. However, the number of the remote sensing derived variables in these studies is very limited compared to the large number of forcing variables required by the crop simulation models. Many forcing variables of the crop simulation models were still unavailable regionally and a limited range of field measurements has therefore been used. Therefore, integrating as much remote sensing information as possible

to a process-based crop simulation model and trying to simplify the requirement of forcing variables of this model are very important for regional crop growth simulation and productivity estimation.

The Breathing Earth System Simulator (BESS) model is a highly simplified remote sensing-derived and biophysical process model. BESS couples the processes of atmosphere (Ryu et al., 2018) and canopy radiative transfer, canopy photosynthesis, evapotranspiration, and energy balance, and has been proven to perform well in estimating GPP (Jiang and Ryu, 2016; Ryu et al., 2011). BESS uses an enzyme kinetic model (Farquhar et al., 1980) to estimate GPP, which offers a more mechanistic interpretation than empirical approaches, such as light use efficiency-based models. As a remote sensing forced process-based model, BESS could provide a comprehensive understanding and description of key ecological processes in agro-ecosystems on global scale and with a spatial resolution of 1 km. However, because it lacks an assimilate allocation module, BESS cannot be applied for crop growth simulation and yield estimation. After filling this gap, BESS could be used as a remote sensing derived process-based crop simulation model, and is expected to be simpler than conventional crop simulation models in terms of variable requirements.

Rice (*Oryza sativa* L.) is one of the three leading food crops worldwide and is consumed by over half of the world's population (Maclean et al., 2013). Under climate change, rice production has become vulnerable to extreme weather events and gradual climate risks (Ainsworth, 2008; Kim et al., 2013; Simelton et al., 2012). Therefore, it is important to accurately simulate growth and estimate the productivity of rice. The existing rice simulation models, e.g. APSIM-ORYZA (Gaydon et al., 2012a,b), CERES-Rice (Singh et al., 1993), and DND-C-Rice (Fumoto et al., 2010) all require dozens of genotype data, soil characteristics, cultivation practices, and meteorological information as forcing variables. Developing a variable-simplified and remote sensing-derived rice simulation model is important for regional rice growth simulation and productivity estimation, and would have further applications in agricultural decision making and climate change research.

The goals of this study were: 1) to develop a remote sensing-derived and process-based rice productivity simulation model, BESS-Rice, by integrating the assimilate allocation module into BESS; 2) to evaluate the accuracy of BESS-Rice by comparing the simulated GPP, dry matter partitioning, and grain yield against *in-situ* measurements at site-level; and 3) to analyze the sensitivity of BESS-Rice to environmental and biological drivers and parameters.

## 2. Material and methods

### 2.1. Overview of sites and data

Three KoFlux rice paddy sites (<http://www.ncam.kr/page/koflux/database/>), distributed from north to south in South Korea, were used in this study (Fig. 1): Cheorwon (CRK; 38.2013°N, 127.2507°E), Cheongmicheon (CFK; 37.1597°N, 127.6536°E), and Gimje (GRK; 35.7451°N, 126.8524°E). Both CRK and CFK have a monsoon and temperate continental climate, with cold and dry winters, and hot summers; GRK has a temperate monsoon climate with marine climate characteristics, with a cold winter and hot summer, without a dry season (Peel et al., 2007). The 30-year mean annual precipitation at CRK, CFK and GRK are 1391 mm, 1371 mm and 1253 mm, and the mean annual air temperature are 10.2 °C, 11.6 °C and 12.9 °C, respectively (Korea Meteorological Administration). The elevation of these three sites are approximately 175 m, 60 m and 21 m above sea level based on the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM), and the soil types are silty clay loam, sandy loam and silt loam based on the national soil database (Hong et al., 2009b) from Rural Development Administration of South Korea. Irrigated japonica (*Oryza sativa* L. ssp. *japonica*) varieties were cultivated at all three sites. These are the predominant rice subspecies

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