Agricultural Water Management 258 (2021) 107183

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

A spatio-temporal analysis of rice production in Tonle Sap floodplains in response to changing hydrology and climate

Manuel Marcaida III [a], Yasmine Farhat [b], E-Nieng Muth [c], Chou Cheythyrith [d], Lyda Hok [c], Gordon Holtgrieve [e], Faisal Hossain [b], Rebecca Neumann [b], Soo-Hyung Kim [a,*]

[a] School of Environmental and Forest Sciences, College of the Environment, University of Washington, Seattle, WA, USA
[b] Dept. of Civil and Environmental Engineering, College of Engineering, University of Washington, Seattle, WA, USA
[c] Center of Excellence on Sustainable Agricultural Intensification and Nutrition and Faculty of Agronomy, Royal University of Agriculture, Phnom Penh, Cambodia
[d] General Directorate of Agriculture, Phnom Penh, Cambodia
[e] School of Aquatic and Fishery Sciences, College of the Environment, University of Washington, Seattle, WA, USA

ARTICLE INFO

Handling Editor - Dr. R. Thompson

Keywords:
Rice production
Hydrology
Remote sensing
Crop modeling
Climate change
Cambodia
Hydropower dams
Mekong river

ABSTRACT

Rice is one of the most important agricultural commodities throughout the Mekong River Basin including the Tonle Sap Lake floodplains in Cambodia. Recent increases in hydropower dams along the Mekong River have likely altered the surface water hydrology impacting the arable areas and soil qualities for rice production in the Tonle Sap lowland. Along with the hydrological impacts, the region's rice farming is facing a rapidly changing climate. It is critical to understand how the hydrological changes associated with dam development impact the region's rice production in a changing climate. The aims of this study were to assess the impacts of recent increases in hydropower dams on the timing and areas of rice cropping in the Tonle Sap floodplains and to evaluate the effects of changing hydrology, rising temperature, and adaptive farming practices on rice productivity using a process-based rice crop model: ORYZA (v3). The effect of dams on arable areas for rice was identified by a remote-sensing method based on the PhenoRice algorithm for the period of 2001–2019 in two rice-growing provinces: Kampong Thom and Battambang. The PhenoRice method identified an increase in rice growing areas as well as shifts in both timing and location of rice cropping towards the sources of irrigation during the dry season since 2010. The ORYZA model simulated a substantial yield reduction with an increase of 2 °C in air temperature in the region. The model predicted that the rice productivity in the region is sensitive to soil organic carbon content which is expected to change with surface water hydrology. The model also predicted that region's rice yield can increase by optimizing the timing and amount of N fertilization. The findings from this study highlight how hydrology, climate, and agronomic practices can interact to impact rice production in the Lower Mekong Region and provide insights for effective water management and agronomic practices to attain food security in the region in a changing climate.

1. Introduction

Rice (*Oryza sativa* L.) is the staple food in Cambodia and rice farming provides livelihood to the majority of the nation's poor population (Cramb et al., 2020; FAO, 2015). About 85% of the country's croplands is cultivated for rice (Siek et al., 2017). Rice production has increased in recent years since the government implemented its policy on "The Promotion of Paddy Production and Rice Export" in 2010 (Royal Government of Cambodia, 2010). Cultivated rice area climbed at a rate of 1.7% from 1990 to 2017 (Cramb, 2020). The country's average yield also improved from 2.5 to 3.3 tons-ha^{-1} from 2005 to 2017 (MAFF, 2018). The Ministry of Agriculture reported a total harvested area of 3.2 million ha in 2018. This boost can be attributed to farmers moving from subsistence to commercial farming, adoption of modern varieties, increased use of fertilizers, mechanization, and availability of credit (Cramb et al., 2020; Johnston et al., 2013; World Bank, 2015a). Cambodian rice is also gaining recognition in the export market for its high eating quality (Sopheap et al., 2018). Despite these developments, Cambodia's yield and production still lags Thailand and Vietnam, its top rice-producing neighbors that also enjoy the irrigation benefits of the

* Corresponding author.
E-mail addresses: manuelpmarcaida@gmail.com (M. Marcaida), soohkim@uw.edu (S.-H. Kim).

https://doi.org/10.1016/j.agwat.2021.107183
Received 23 February 2021; Received in revised form 9 September 2021; Accepted 13 September 2021
Available online 24 September 2021
0378-3774/

rich Mekong River ecosystem (Smith and Hornbuckle, 2013; USDA, 2010; World Bank, 2015a).

Large portions of rice in Cambodia are cultivated around the Tonle Sap floodplains. Approximately 23% of the floodplains are used for agriculture, for which 75% are used for rice production (FAO, 2015; Matsui et al., 2006). The Tonle Sap Lake is the largest and most important lake in the Lower Mekong Region in South-East Asia. It is often referred as the beating heart of Cambodia with its cyclic swelling and shrinking during the annual transition from monsoon to dry season (Lamberts, 2006). Tonle Sap Lake connects to the Mekong River through the 110 km Tonle Sap River (Eyler and Weatherby, 2019). As the Mekong River brings intense monsoon floods from May to October, it carries an abundant mix of organic matter, nutrient-rich sediments, and diverse fish species that are deposited to the Tonle Sap floodplains (Eyler and Weatherby, 2019). At its peak, the lake can increase six times larger than its dry season volume. Depth goes from 1 to 10 m or more, of which 70% of the water comes from the Mekong River (Matsui et al., 2006). As the floods recede during the dry season, the floodplains become a spawning ground for fishes and provide a fertile soil for crop production (Eyler and Weatherby, 2019; Hortle et al., 2004; Lamberts, 2006).

Hydrology in the Tonle Sap floodplains is changing because of the increasing number of dams in the Mekong River and tributaries regulating the flood flow downstream (Pokhrel et al., 2018a). While dams and hydroelectric power plants are built to address the increasing energy demands the Lower Mekong, they also alter the natural cycle of biota exchange between Tonle Sap and Mekong River (Sabo et al., 2017; Stone, 2016). Currently, the connectivity of the floodplains to the river already reduced by 31% (Eyler and Weatherby, 2019). Previous studies already predicted that lake extent and depth during dry season could increase (Haddeland et al., 2006; Kummu and Sarkkula, 2008; Mekong River Commission, 2010; Pokhrel et al., 2018b) and consequently drive irrigation infrastructure development (Arias et al., 2012). Better access to irrigation could influence planting time and open more lands for rice farming. However, the impact of changing Tonle Sap hydrology to rice production in terms of area, location, and timing of cultivation has not yet been examined.

Water availability is a major constraint in dry season rice production in Cambodia. Paddy fields situated farther away from rivers and canals are likely to experience water stress according to a study conducted by Veasna et al. (2014). However, with hydropower dams regulating the flow of stored flood water from the monsoon months, water level is expected to rise and reside longer during the dry season (Arias et al., 2012; Kummu and Sarkkula, 2008; Mekong River Commission, 2010; Pokhrel et al., 2018b). Several infrastructure projects are currently initiated to allow better access to dependable irrigation (ADB, 2019; ACIAR, 2015). Although MAFF (2018) already reported the increasing dry season rice production area, information on the location and timing of the expansion are scarce.

As climate is changing, drought spells are occurring more frequently in Cambodia, specifically in 2002, 2012, 2015 and 2016 (Sithirith, 2017). The country's mean temperature has increased at a rate of 0.02 °C annually since 1950 (Thoeun, 2015). By 2060, the mean annual temperature is predicted to increase by 2.7 °C (World Bank, 2018). Dry season monthly average temperature of Tonle Sap Lake is rising by 0.03 °C each year from 1988 to 2018 (Daly et al., 2020). Comprehensive water management and forecasting in the Lower Mekong Region is critical in making important decisions related to food security. For instance, with the presence of dams, providing guidelines on the amount and timing of discharge will aid in ensuring irrigation demands are met in the rice cropping areas.

The soil organic matter of the agricultural zone of Tonle Sap's floodplains is replenished by the rich mix of sediments from the monsoon flood. Dry season rice benefits from this ecosystem service once the water subsides, leaving behind fertile silt deposits (Eyler and Weatherby, 2019). In a comprehensive survey conducted by Arias et al. (2013), they determined positive correlation between organic matter content and duration of inundation. As the dams continue to control the magnitude of water and sediment flow (Beveridge et al., 2020; Kondolf et al., 2014), the nutrient quality carried by the flood pulse during the wet season could diminish. This might result in less fertile deposits in the floodplains come dry season, making it even more necessary for farmers to apply chemical fertilizers.

In the absence of long-term yield and production data, earth observation acquired from satellite images can provide information on how rice production patterns in Tonle Sap floodplains have changed over the years. Rice cropping areas can be identified by detecting agronomic flooding during the start of the season and subsequent ground cover changes corresponding to rice phenological stages displayed by the vegetation index. Such indicators are the basis of the PhenoRice algorithm (Boschetti et al., 2017), which utilizes hypertemporal optical imagery from Moderate Resolution Imaging Spectroradiometer (MODIS) to map rice areas (NASA Goddard Space Flight Center, Ocean Ecology Laboratory, 2014a, 2014b). The method identifies signals of crop establishment and key phases of development of the rice plant. Effects of climate and agronomic variables that contribute to rice yield and production can be explained using process-based crop models (Boote et al., 1996; Rosenzweig et al., 2014). The ORYZA (v3) Rice Model (Bouman et al., 2001; Li et al., 2017) was specifically designed to simulate rice growth and development. The model can estimate the effect of climate, soil carbon and nitrogen dynamics, irrigation, and farm management practices to harvest yield at varying rice production environments (Belder et al., 2005; Boling et al., 2007; Radanielson et al., 2018; Sudhir-Yadav et al., 2011). When actual ground data are not available, remote sensing and crop modeling can provide area-based historical yield estimates and generate yield forecasts for future scenarios.

This study examined the changes in the dry season rice production in the Tonle Sap floodplains coinciding with the surge of hydropower dam developments in the Mekong River. Using remote sensing, we analyzed the relationship between cropping patterns and surface water availability. Through crop simulation modeling, we investigated the effects of climate change, farm management practices, and field abiotic conditions to harvestable rice yield. Specifically, this research sought to accomplish the following objectives: 1) to detect the changes in timing and location of cropping before and after the surge of dam developments using the PhenoRice method and 2) to test and apply the ORYZA (v3) Rice Model in simulating the effect of changes in hydrology, agronomic practices, and increasing temperature to rice production and yield.

2. Materials and methods

2.1. Spatio-temporal changes in crop production

Based on the study by Hecht et al. (2019), dam constructions in the Lower Mekong River dramatically increased from 2010 and beyond (Fig. 1), therefore we designated 2001–2010 as "pre-dam" and 2011–2019 as "post-dam", which in this paper referred to as "dam-periods". There were 37 operational hydropower dams in the Mekong River basin in 2010 and this number increased to 64 by 2017 (Hecht et al., 2019).

2.1.1. Study sites

This study focused on Kampong Thom and Battambang, two of the major rice-producing provinces in Cambodia (Fig. 2). In 2017, MAFF reported that Battambang contributed 1.15 million tons (11.0%) and Kampong Thom shared 0.80 million tons (7.9%) to the country's total rice production. In the same year, Kampong Thom and Battambang accounted for 9.81% and 3.74% of the total dry season production area, respectively. The dry season rice production spans from October to March. Direct-seeding by manual broadcasting is the common sowing practice (Nesbitt, 1997). Rice growers in these provinces rely on irrigation systems for water source during the dry season. Canals and

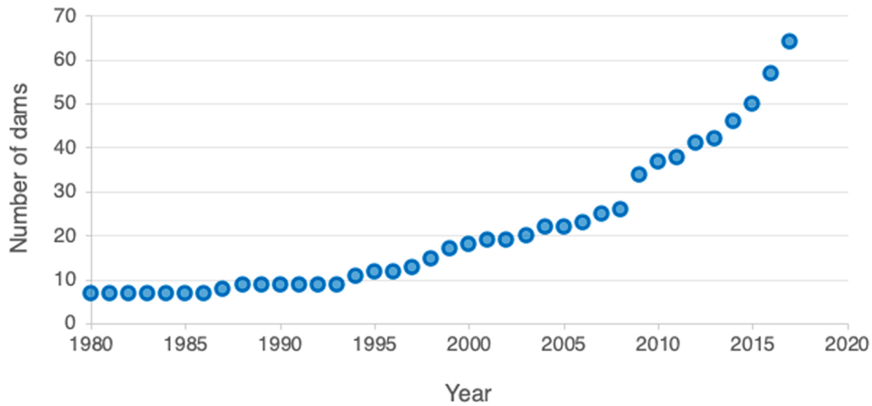

Fig. 1. Mekong River dam inventory from published article by Hecht et al. (2019) showing the rapid increases in the number of hydropower dams from 2001 to 2017. This is the basis for delineating the “dam periods” in this paper into “pre-dam” (2001–2010) and “post-dam” (2011–2019).

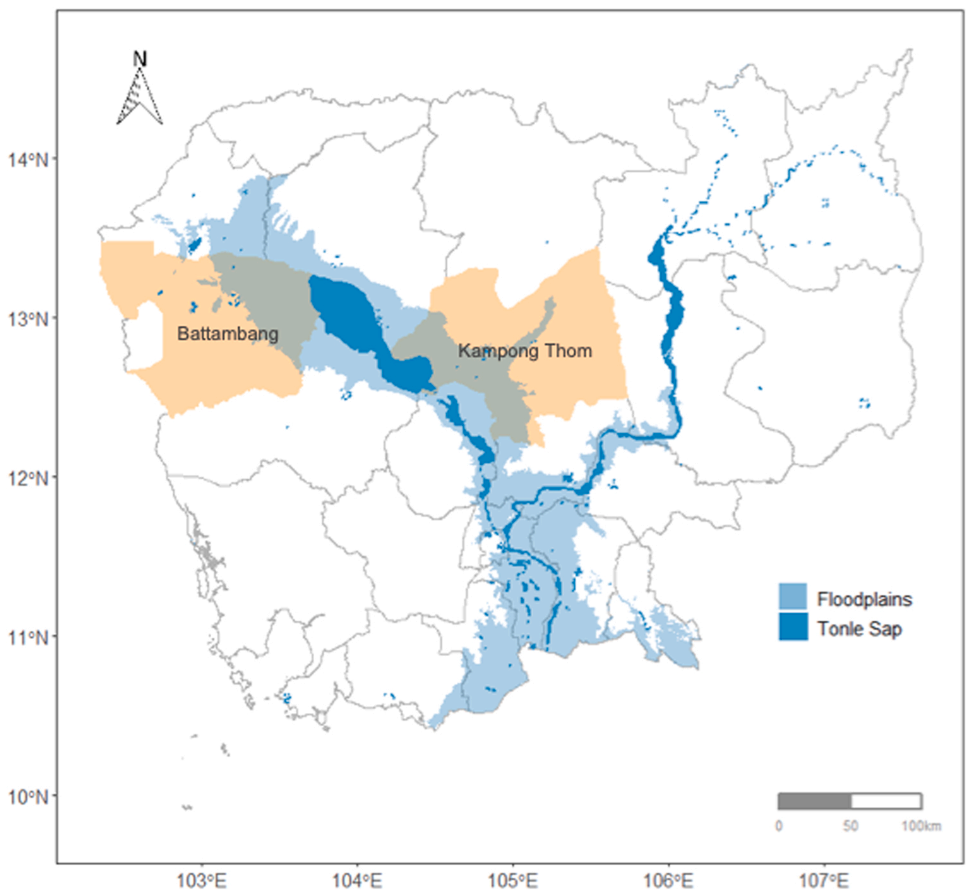

Fig. 2. Geographical map of the study sites overlaying the permanent extent of Cambodia’s Tonle Sap Lake during the dry season rice production and the maximum observed flood extent during the monsoon season since 2000.
(Source: OpenDevelopment Cambodia, 2017).

reservoirs distribute the remaining monsoon water in the Tonle Sap Lake to the rice-growing areas (Cramb et al., 2020; Smith and Hornbuckle, 2013).

Kampong Thom is in the central part of Cambodia, close to the confluence that connects the lake to the Mekong River, exposing it to early and prolonged inundation (Fig. 2). Much of its locality lies in the southeastern part of the Tonle Sap floodplain where 94% of agricultural lands are devoted for rice farming (ADB, 2012). Dry season rice is commonly planted in the latter part of the wet season to early dry season, which is around September to November (Cramb et al., 2020; Ricepedia, 2018). Battambang is situated in the northwestern part of Cambodia and by the northern end of the Tonle Sap Lake (Fig. 2). In the western side of the province is the Kamping Pouy Reservoir, providing good water management system for the rice growers within the area (Nguyen et al., 2011; Sithirith, 2017). It has one of the largest irrigated paddy rice areas in the country (Siek et al., 2017) and the top producer of wet season rice. The locations of these two provinces provide perspective on the rice cropping pattern, from the start of the monsoon until the flood recedes in the dry season. Kampong Thom experiences early and longer flooding while Battambang experiences late inundation and early flood recession.

2.1.2. Detecting the timing and location of cropping using PhenoRice

The PhenoRice method identifies rice cropping areas on a per-pixel basis by thresholding vegetation indices and derivative curve fitting (Boschetti et al., 2017). This allows the recognition of key phenological stages such as sowing, flowering, and planting duration. It also detects signals of agronomic flooding before and after crop establishment to confirm a rice area. The algorithm has been tested over different genetic, environmental, management, and climatic conditions with high detection of accuracy (Boschetti et al., 2017; Busetto et al., 2019; Setiyono et al., 2018).

Phenological indicators are distinguished by using the Enhanced Vegetation Index (EVI) and Normalized Difference Flood Index (NDFI) from the MODIS Terra and Aqua (MOD13Q1 and MYD13) time-series images (Busetto and Ranghetti, 2016; NASA Goddard Space Flight Center, Ocean Ecology Laboratory, 2014b, 2014a). As a rule, a pixel is classified as a rice area if a clear and unambiguous flood condition is detected based on the defined NDFI threshold. The flood signals should be followed by EVI profile consistent with the rice's development stages to discriminate from other flooded habitats (Boschetti et al., 2017; Busetto et al., 2019). Rapid growth during the vegetative stage of the plant is indicated by the increase in EVI signal, followed by a relatively stationary peak that signifies anthesis, and finally the decrease in spectral curve slope that represents senescence and harvest. Savitzky-Golay smoothing (Chen et al., 2004) was applied to reduce noise and substitute missing pixels of the EVI and NDFI time series. The highest minima of the EVI spectral curve closest to the detected agronomic flooding is a proxy to crop establishment while the highest maxima correspond to crop heading. The MODIS time-series Day of Year (DOY) product, which gives the Julian date when the image was acquired, aids in identifying the dates when these important signals occur allowing us to estimate crop establishment or planting time. Usefulness Index and Pixel Reliability indicators were used for quality control, especially the inherent error expected for the monsoon season where cloud covers and rain are a common occurrence. The complete description of this method is provided by Boschetti et al. (2017) and implemented as an Interactive Data Language in ENVI® (Exelis Visual Information Solutions, Boulder, Colorado), a software for geographical and remote sensing imagery analysis. In this study, the PhenoRice workflow (see Appendix A) was coded and executed in the statistical software R (R Core Team, 2020).

The required parameters were calibrated by applying PhenoRice to the 17 farms visited in Kampong Thom and Battambang. Length of vegetative stage and planting durations were based on the commonly used rice varieties on these sites. Medium-duration (~100–110 days) varieties were assumed for dry season planting. Flooded conditions, which suggest land preparation and crop establishment, have a minimum threshold NDVI value of 0.

Earth observation images from MODIS Terra and Aqua have 250-m spatial resolution and 8-day combined nominal temporal resolution. These products have been widely-used for modeling terrestrial ecosystems to detect long-term land-use and cover changes. Time-series EVI (Huete et al., 1994), NDFI (Boschetti et al., 2014), DOY, Usefulness Index, and Pixel Reliability quality indicators were the specific products used as input for PhenoRice. They were preprocessed and extracted using the MODIStsp package (Busetto and Ranghetti, 2016) in R. Annual land cover maps downloaded from SERVIR-Mekong (https://rlcms-servir.adpc.net/en/landcover/) were used to pre-classify rice areas before implementing PhenoRice.

Crop establishment dates estimated by PhenoRice from 2001 to 2019 were recorded, with the corresponding pixel count and location. The planting dates were used as input in ORYZA (v3) to estimate the total rice production (tons ha^{-1}). The total area for a given crop establishment date were calculated for each dam-period. The time-series moving average was obtained with 8-day rolling window, accounting for the temporal resolution of the MODIS images. We plotted the geo-coordinates of the pixels and created a density map to spatially illustrate the locations and clustering of farm areas.

2.1.3. Estimating changes in flooding extent using NDFI

The changes in dry season hydrology in the Tonle Sap Lake were estimated through remote sensing, where water areas were detected using NDFI signals. A fixed area extent to delineate Kampong Thom and Battambang was designated for each analyzed image from 2001 to 2019. An area is flooded if the pixel has a minimum value of 0 (Boschetti et al., 2017). The percentage of flood pixels for a given extent and associated DOY were obtained. The moving average of percent flooding during pre-dam and post-dam were calculated with an 8-day rolling window, based on the temporal resolution of NDFI and DOY images. The relationship between the extent of flooding with the timing and area of cropping were evaluated using pair-wise comparison and Pearson correlation, respectively. Note that NDFI only detects surface water, thus that depth of flooding was not considered in the analysis.

2.2. ORYZA (v3) model calibration and testing

All the production and yield estimations in this study were executed using the ORYZA (v3) Rice Model (Li et al., 2017), formerly known as ORYZA2000 (Bouman et al., 2001), developed at the International Rice Research Institute (IRRI). This recently updated version has an expanded ability to model lowland, upland, and flooded rice ecosystems. It mechanistically simulates growth and development of rice through its photosynthesis, respiration, and water-nitrogen balance modules. Its capability to model weather, agronomic management conditions, and abiotic constraints has been calibrated and validated for 18 popular rice varieties in various locations throughout Asia (Belder et al., 2005; Boling et al., 2007; Li et al., 2015; Radanielson et al., 2018; Sudhir-Yadav et al., 2011). The model update features the soil carbon and nitrogen dynamics module that quantify the changes in the soil organic carbon and nitrogen content. The soil temperature module was also added, which accounts for the daily temperature from the soil surface to the lower layers. The detailed formulations behind these modules can be found in Li et al. (2017).

To test the ability of the crop model to simulate farm conditions within our specific study region, we calibrated and tested ORYZA (v3) using field measurements and information gathered from farmer's interviews during the dry season of 2018 and 2019. There were two rice varieties commonly planted in our sample farms. One is Sen Kra Ob, with short-to-medium planting duration, aromatic, and commonly grown for the export market. The other variety was IR 5154, which has a longer growth duration and cultivated in both dry and wet seasons. These two varieties were calibrated using the measured total dry biomass and phenological information to determine their specific leaf area and partitioning factors (Appendix B). The values were calculated using the auto-calibration tool in the ORYZA (v3) model package. All the other crop parameters were taken from the default crop values of the model, which are based on the robustly parameterized IR 72 rice variety. Model testing was conducted by comparing the measured total dry biomass, stem, and leaf measurements in the vegetative stage of the 2019 dry season to the simulated values. Associated R^2, root mean square error (RMSE), relative root mean square error (rRMSE), and model efficiency (EF) were duly noted to determine the predictive accuracy of the simulation outputs. The following formula were used to calculate RMSE, rRMSE, and EF:

$$RMSE = \sqrt{\frac{\sum_{1}^{N}(y_i - Y_i)^2}{N}} \tag{1}$$

$$rRMSE = \frac{RMSE}{\bar{y}} * 100 \tag{2}$$

$$EF = 1 - \frac{\sum_{1}^{N} (y_i - Y_i)^2}{\sum_{1}^{N} (y_i - \bar{y})^2} \quad (3)$$

Observed values are designated by y_i and simulated values by Y_i. The total number of samples is given by N and $\bar{y}$ is the mean of observed values.

2.2.1. Farm surveys and interview with growers

We conducted interviews with local growers to collect baseline data for model calibration and testing. Sowing date, irrigation depth, amount and timing of fertilizer application, and growth stage information of the planted variety were noted. Sizes of the farms included in the study ranged from 0.2 to 3.0 ha. We visited 12 farms in Krong Stueng Saen Village in Kampong Thom near the Stung Sen River, a tributary of Tonle Sap Lake. The sample farms were selected such that their spread represent the elevation gradient and distance from the lake. During our interviews, we gathered that irrigation is managed by a local farmers cooperative under the Cambodia Agricultural Value Chain (CAVAC) program. Although these farms are located no more than 10 kilometers apart, their crop establishments varied according to their proximity to irrigation sources. Farms located farther away from the river tend to sow early to utilize the receding monsoon flood. In Battambang, we collected data from five farms located in Banan District. Their irrigation is controlled by the local government through the Provincial Department of Water Resources and Meteorology as verified during our interviews. Thus, their sowing times could vary from two weeks to one month.

It was an unusually dry year in Cambodia in 2019. For instance, Kampong Thom farmers had to plant early to take advantage of the subsiding lake water from the dry monsoon season. Most of the rice farmers in Battambang suspended sowing because there was no available irrigation. We were informed during the farm visit that the local government decided to reserve the water supply for the anticipated drought for the rest of the dry season in 2019. The farms we visited in Kampong Thom appeared to have greater flexibility and capacity to make decisions related to irrigation management compared to the Battambang sites who are reliant on the local government for the release of water to the canals.

2.2.2. Plant biomass measurements

Weight of total biomass and planting density were taken at reproductive stage in DS 2018 (January to February, 2019). Samples were taken from three replicates of 0.5 × 0.5 m quadrat spread out to represent each farmer's plot. Total number of tillers per quadrat were noted and 20 subsamples were oven-dried at 75 °C for at least 3 days. Fresh and dry weight of the 20 subsampled tillers were measured. During the vegetative stage in DS 2019 (December, 2019), weight of partitioned biomass and planting density were measured. Weeds were observed to be a common problem in the paddies, occupying up to 20% of the cropping area based on visual estimation in the farms visited.

2.2.3. Soil measurements

Soil measurements were taken by core boring at 0–15 cm depths. Soil texture was determined by hydrometer method adapted from Huluka and Miller (2014). Total N was analyzed by Kjeldahl digestion method (Greweling and Peech, 1960; Jackson, 1959). Total soil organic carbon was measured following Ghani et al. (2003). Bulk density was determined from soil sampled at 5 cm depth using a metal tube with 5 cm diameter (Costantini, 1995). Soil texture, total N, soil organic matter content, and bulk density measurements were used as input data for crop model simulations. All plant and soil samples were processed at the Soil Science Laboratory of the Royal University of Agriculture in Phnom Penh, Cambodia. Other required parameters, such as the different volumetric water contents and saturated hydraulic conductivity, were estimated following the derivation formulated by Saxton and Rawls (2006). To provide the 100 cm depth soil information required by the crop model, soil texture, soil organic carbon, and bulk density from 15 to 100 cm depth were obtained from SoilGridsTM (https://soilgrids.org). This online resource is provided by the World Soil Information (also known as the International Soil Reference and Information Centre) generated from global compilation of soil profile data and environmental layers through machine learning methods at 250 m^2 resolution. Other input data required by ORYZA (v3), such as volumetric water content and hydraulic conductivity, were derived based on Saxton and Rawls (2006) from the soil texture information provided by SoilGridsTM.

2.2.4. Climate data

Climate data for model calibration and farm-specific dry season simulations in 2018 and 2019 were provided by the weather stations from Cambodia's Center of Excellence on Sustainable Agricultural Intensification and Nutrition (CESAIN). Since historical weather data from 2001 to 2018 were unavailable for Battambang and Kampong Thom, we obtained the temperature, solar radiation, vapor pressure and wind speed data from the National Centers for Environmental Prediction Global Forecast System (NCEP GFS). Rainfall data from Tropical Rainfall Measuring Mission (TRMM 3B42V7) were resampled to 0.1 degree (~10 km) spatial resolution. The estimated climate data from GFS and TRMM were used for seasonal yield simulations performed from 2001 to 2018.

2.3. Scenario simulations

ORYZA (v3) simulates rice growth at daily time step, requiring crop, soil, field management, and weather input data. Crop data includes the genetic characteristics of the variety used, such as phenology, development rates, assimilate partitioning behavior, among others. Soil input information includes soil texture, chemical composition, and water content. Agronomic management inputs required are crop establishment method, timing/density of planting, and timing/amount of applied irrigation and nitrogen (N). Daily weather data includes temperature, solar radiation, vapor pressure, wind speed, and rainfall. We used the model to estimate the final yield based on the planting date we obtained from PhenoRice, as well as to simulate yield responses due to changes in temperature, N application, and soil nutrient deposits in the form of organic carbon.

2.3.1. Estimating past production and yield

We calculated the attainable yield for each sowing date from 2001 to 2018 to capture the changes and effects of climate conditions to the total. In this context, attainable yield is the highest possible yield that the model can predict from the given inputs and abiotic conditions (Sadras et al., 2015). Same management inputs were employed through all the simulations, which were based on the agronomic practices of the visited farms in Kampong Thom with median harvest yield. Essentially, the only varying factors were the historical daily weather information obtained from NCEP GFS and TRMM 3B42V7. Using the total rice area per planting date from PhenoRice and yield from calibrated IR 5154 variety, we estimated the mean daily total production for pre-dam and post-dam periods.

2.3.2. Predicting yield response to changes in temperature, nitrogen applications, and residual soil organic carbon

Upon determining the level of confidence of ORYZA (v3) to simulate the actual field conditions in our farm samples, we performed sensitivity analysis by designing a range of treatments to model yield response. All simulations were executed using field conditions and farmer's practices gathered from the Kampong Thom farms during the 2019 dry season (Appendix C).

2.3.2.1. Temperature effects. In 2015, Cambodia recorded a maximum annual temperature of 38 °C (Thoeun, 2015). Furthermore, the World Health Organization (WHO) predicted that Cambodia's yearly average could increase from 1.6 to 2.0 °C by 2100 (WHO, 2016). Given these conditions, we estimated the effect of supra-optimal temperatures on the harvest yield of the sample farms in Kampong Thom farms. We simulated changes of − 5 to 5 °C from the daily temperatures recorded by CESAIN weather station. In addition, a long-term simulation experiment was performed to explore the rice yield sensitivity to temperature increases and whether this increase would affect the ideal planting times in the future climate. This simulation experiment was done by adding 3 °C to the base air temperatures in the weather data for the period of 2001–2018. The temperatures used in these simulations were meant to capture extreme temperature changes, higher than the predicted by WHO.

2.3.2.2. Nitrogen application effects. We performed N simulations with three application schedules based on our farm interviews (Appendix C), with total N applied ranging from 30 to 200 kg-ha^{-1} per season. In the first simulation (S-1) N was applied at two different developmental stages: 1) during early tillering and 2) panicle initiation; in the second simulation (S-2) N was also applied twice: 1) during late tillering and 2) booting; and lastly (S-3) simulated three N applications: 1) during early tillering, 2) late tillering, and 3) panicle initiation.

2.3.2.3. Residual soil organic carbon. In anticipation of the decline of sediment quality in the Tonle Sap floodplains, we estimated the possible effects of the changing soil organic carbon (SOC) content to the harvest yield. Referencing the onsite SOC measured during the start of dry season in 2018, we estimated the final yield if SOC is decreased by up to 50% or increased to up to 50% using the calibrated IR 5154 variety.

2.4. Data processing and statistical analysis

The MODIS time-series satellite data from 2001 to 2020 were extracted from the National Aeronautics and Space Administration archive (NASA Goddard Space Flight Center, Ocean Ecology Laboratory, 2014b, 2014a) and pre-processed in R language (R Core Team, 2020) using the 'MODIStsp' package (Busetto and Ranghetti, 2016). The PhenoRice algorithm was written and implemented in R with the aid of GIS and remote sensing packages such as 'rgdal' (Bivand et al., 2021), 'raster' (Hijmans and Van Etten, 2012), 'rgeos' (Bivand et al., 2021) and 'sf' (Pebesma, 2018). Further data processing and statistical analyses such as student *t-test*, correlation, ANOVA, and Savitzky-Golay smoothing were undertaken using 'tidyverse' (Wickham et al., 2019), 'hydroGOF' (Zambrano-Bigiarini, 2020), 'prospectr' (Stevens and Ramirez-Lopez, 2020), and 'base' (R Core Team, 2020) packages in R. (Table 1).

3. Results

3.1. Lake water extent in relation to location and timing of rice production

The almost two-fold increase in hydropower dams in the lower Mekong River since 2010 coincided with apparent shift in timing and location of rice cultivation to later in the year, especially for Kampong Thom province. To graphically illustrate the influence of the floodwater availability to the crop establishment distribution in the dry season production (October to January), we overlaid the rolling average of the surface water detected in the Tonle Sap Lake with the average percent of rice area planted (Fig. 3, area in blue). We performed simple pair-wise comparison on the seasonal and monthly flood extent between pre- and post-dam periods. The percent water area detected in the designated map extent per province during the two dam periods were compared

Table 1
PhenoRice parameters for identifying the locations and planting dates of rice areas in Kampong Thom and Battambang. Values were calibrated based on the time-series satellite images of sample farm locations visited in 2018 and DS 2019 dry season.

Datasets and Parameters	Values	Units	Description
Pre-dam	2001–2010	years	Years before increased presence of dams
Post-dam	2011–2019	years	Years of increased presence of dams
Dry season	1 October - 31 January	–	Possible planting periods
EVI_{min_th}	0.35	–	Maximum lowest value of EVI to be considered as sowing period
EVI_{max_th}	0.40	–	Minimum highest value of EVI to be considered as anthesis
$NDFI_{th}$	0	–	Minimum threshold of NDFI to indicate flooded conditions
win_{decr}	90	days	Maximum difference between identified anthesis and possible harvest period
$decr_{th}$	55	%	Percent decrease in EVI_{min_th} and EVI_{max_th} to estimate harvest period
Δt_{min}	35	days	Maximum difference between identified sowing period and possible anthesis
Δt_{max}	110	days	Maximum difference between identified sowing and possible harvest period

(Table 2). Based on student t-test, there was no significant difference between the seasonal area of flooding of the two dam periods in both Battambang and Kampong Thom (Table 2). However, monthly flood variability showed statistical increase in surface water at post dam period, specifically in the months of November and January for both in Kampong Thom and Battambang floodplains (Table 2).

Examining the cultivated rice areas detected by PhenoRice, there was an apparent shift in crop establishment schedule as shown by the difference in plot areas in Fig. 3 (area in green and yellow). Pairwise comparison between pre-dam and post-dam periods showed significance difference on the estimated monthly total rice area (Table 3). Increase in rice cultivation during post-dam period was more evident in Kampong Thom, specifically from November to December. Previously at pre-dam, sowing falls on early October, the onset of the dry season.

In the case of Battambang province, the results of a two-tailed student *t-test* in Table 3 did not show statistical significance in the seasonal rice areas between pre-dam and post-dam. However, extended crop establishment was observed in November to December during post-dam period.

PhenoRice allowed us to examine the spatial distribution of rice farms in the Tonle Sap floodplains, illustrated by the density maps of the different planting seasons in Fig. 4. The heat map of Kampong Thom showed that farms were more clustered during pre-dam and became sparsely distributed during post-dam and (Fig. 4, A and B). In Battambang province, the locations and area distribution were generally similar for both pre- and post-dam (Fig. 3, C and D). Cropping was relatively denser during pre-dam on the northwest side where Kamping Pouy reservoir is situated, however, an apparent decrease in hotspot density can be observed during the post-dam period. Concentration near the reservoir declined while cultivations seemed to shift towards the direction of the lake.

To establish the relationship between the area of inundation and area of rice cultivation, a simple correlation was performed between the seasonal flooding detected and total seasonal rice area (Table 4). The seasonal flooding was the mean of the surface water detected by NDFI each year for the entire dry season, while the total seasonal rice area is the mean of the annual sum of dry season rice areas estimated by PhenoRice. In Kampong Thom, there was a strong correlation between the extent of flooding and rice area planted (0.81) at pre-dam. However, this

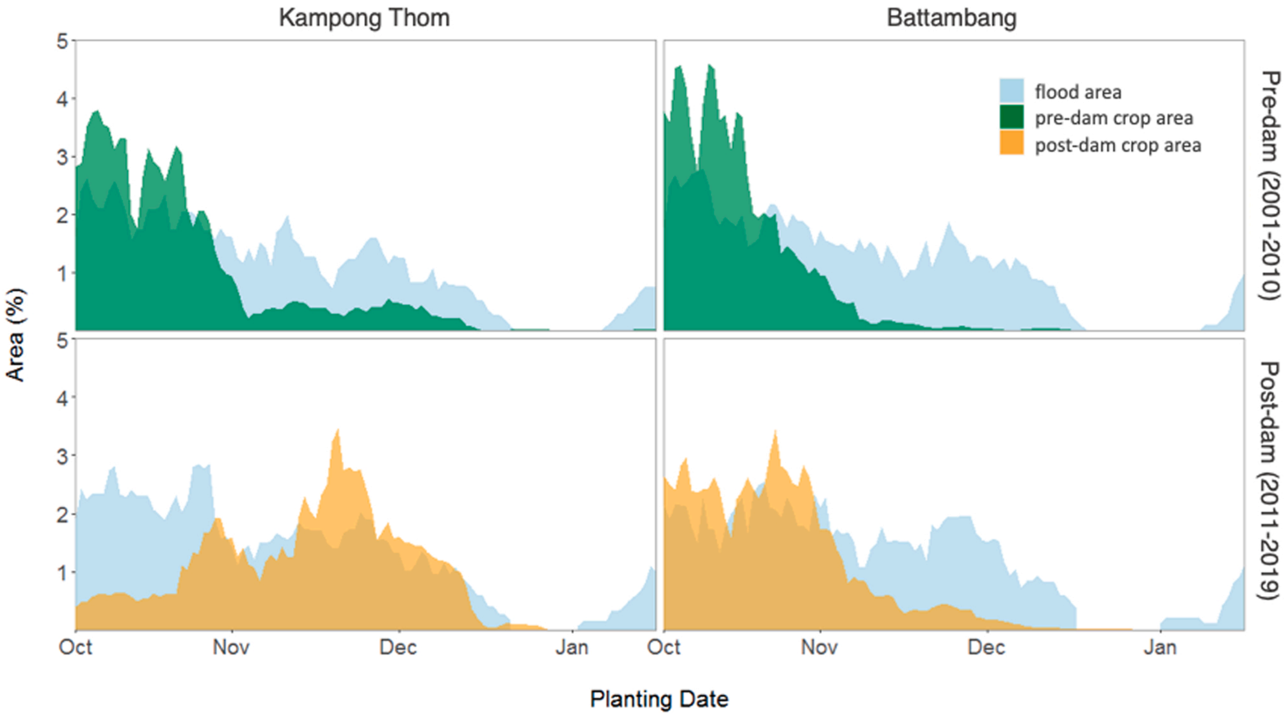

Fig. 3. Relationship between flooding extent and timing of crop establishment in Kampong Thom and Battambang province at pre-dam (2001–2010) and post-dam (2011–2019) periods. Flooding extent (area in blue) was estimated using the MODIS NDFI time series products, calculating the 8-day rolling average percentage of inundation detected. Sowing area is the 8-day rolling average percentage of cultivated rice estimated by PhenoRice.

Table 2
Pair-wise comparison between pre-dam (2001–2010) and post dam (2011–2019) surface water area detected by NDFI signals. Comparisons were made per season and monthly basis.

Season/ Month	Kampong Thom (% surface water)			Battambang (% surface water)		
	Pre-dam	Post-dam	Significance	Pre-Dam	Post-Dam	Significance
Dry season percent surface water	1.08	1.26		1.13	1.25	
October	2.00	2.25	**	2.04	2.07	
November	1.35	1.58	***	1.39	1.65	***
December	0.47	0.56		0.48	0.50	
January	0.45	1.33	***	0.53	1.30	***

*p ≤ 0.05; ** p ≤ 0.01; *** p ≤ 0.001

correlation decreased at post-dam (0.49) as shown in Table 4. As the correlation decreased, significant increase in cultivation (Table 3) and fairly spread-out distribution of planting locations along the floodplains (Fig. 4, A and B) were observed at post-dam in Kampong Thom.

Conversely in Battambang, the correlation between flooding extent and planting area remained high and increased slightly at post-dam (0.71–0.74). As the extent of the lake increased in November and December at post-dam (Table 2), so did the area of rice cultivation (Table 3). There was no considerable change in the location of planting in Battambang but subtle movement of high-density areas towards the location of the lake was evident in Fig. 4 (C and D).

3.2. Results of crop model calibration and testing

Total dry biomass of IR 5154 and Sen Kra Ob sampled in 2018 were used for model calibration. Total and partitioned biomass sampled in Kampong Thom in 2029 were used for model testing. Only IR 5154 variety was used for model testing because inadequate data for Sen Kra Ob. Results are shown in the 1:1 plot in Fig. 5 to visually inspect the differences between the modeled and actual measurements. The corresponding values of the goodness-of-fit parameters are listed in Table 5. The calculated modeling efficiency (EF) for model calibration was 0.49 and 0.64 for IR 5154 and Sen Kra Ob, respectively. A model is considered acceptable if threshold values are 0.5 < EF (Moriasi et al., 2007). Other parameters, such as RMSE, rRMSE, and R^2, were used to verify the ability of the model to predict biomass and yield from actual farm conditions (Table 5). The total biomass during the more advanced stage of development were underestimated, but overall model testing showed acceptable EF and R^2. Partitioned green leaves and stem gave EF values of 0.56 and 0.35, respectively.

Tablee 3
Mean comparison of the total rice areas estimated by PhenoRice between pre-dam (2001–2010) and post-dam (2011–2019) periods.

Season/Month	Kampong Thom (x100 ha)			Battambang (x100 ha)		
	Pre-dam	Post-dam	Significance	Pre-Dam	Post-Dam	Significance
Dry season total rice area	27.39	82.84	***	109.77	117.08	
October	22.81	20.96		102.09	91.34	
November	2.83	44.85	***	7.19	23.99	**
December	1.30	16.64	**	0.49	1.75	*
January	0.05	0.00	***	–	–	

*p ≤ 0.05; ** p ≤ 0.01; *** p ≤ 0.001

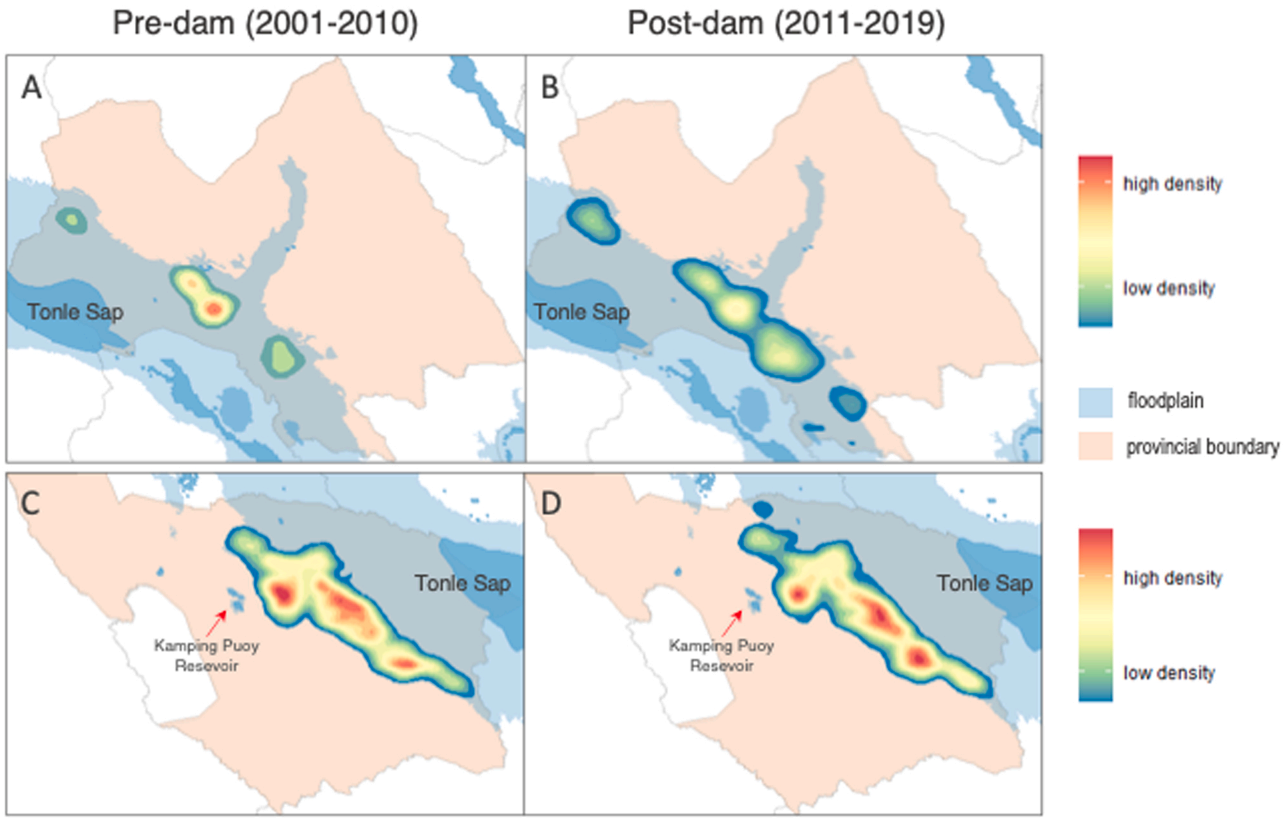

Fig. 4. Heat maps of estimated cultivated rice areas by PhenoRice showing the locations and clustering of farms in Kampong Thom (A, B) and Battambang (C, D) during the dry season at pre-dam (2001–2010) and post-dam (2011–2019) periods. Due to their location in the Tonle Sap Lake, Kampong Thom experiences early and longer flooding while Battambang experiences late inundation and early flood recession. Note that the floodplain extent is only for illustration purposes and not representative of the flooding detected by NDFI in Fig. 3.

Table 4
Pearson correlation between the seasonal flooding extent detected by NDFI and the total rice cultivation areas estimated by PhenoRice at pre-dam (2001–2010) and post-dam (2011–2019) periods.

Farm Site	Pre-Dam (2001–2010)	Post-Dam (2011–2019)
Kampong Thom	0.81	0.49
Battambang	0.71	0.74

3.3. Modeling production from historical climate conditions

Combining remote sensing and crop modeling, we observed considerable increase in total rice production during the post-dam period in Kampong Thom province. This can be expected since rice areas noticeably increased, based on the results of PhenoRice method (Fig. 6). Crop establishments at pre-dam period were concentrated in October with relatively less production activities for the rest of the dry season. Noticeable shift in planting time is observed during post-dam, particularly in the months of November to December.

Yields trends in pre- and post-dam periods follow the same pattern, as represented by solid continuous line in Fig. 6. The dry season attainable yield of IR 5154, the variety used in the simulation, fluctuated between 6.5 and 7.0 tons-ha^{-1}. The seasonal variability was primarily driven by the climatic conditions during the plant's growth and development. Note that for these simulations, historical weather data were used, and same farm management inputs were assumed regardless of the planting date.

The annual total production for the sample provinces were estimated and presented in the bar graph in Fig. 7. The only available official data gathered from MAFF for the two sample provinces was for 2016 and 2017, represented by the points in the graph. This very low number of data points were inadequate to substantially validate the 17-year production data estimated by the model. From these two production data points, there was noticeable underestimation by the combined PhenoRice and ORYZA (v3), which would also be true for the previous years where official data were not available. Fluctuations in the total dry season annual production was also evident in the modeled results instead of a slow steady increase that is displayed by the production growth from MAFF reports (MAFF, 2017, 2018). Potential reasons for this underestimation are addressed in the discussion.

3.4. Simulating potential future conditions

3.4.1. Amount and timing of N application

The model estimated that a total optimum N of 150 kg-ha^{-1} was required for IR 5154 to reach its maximum attainable yield. Regardless of the treatment, no apparent yield advantage was observed for any N applied greater than 150 kg-ha^{-1}. Treatments S-1 and S-2 tend to score higher yield than S-3 in sub-optimal N conditions. For S-1 and S-2, N was applied two times during the growing period while N was applied three times for S-3.

3.4.2. Soil organic carbon

During our soil sampling, the measured SOC in the farms varied from 0.3 to 0.8 g-kg^{-1} at 0–15 cm depths, which fall in the low fertility category. Three treatments based on the management practices observed in the sample farms were simulated. The treatments were identified as follows: low, refers to the practices that produced the lowest reported yield; medium for the median yield; and high for the management that obtained the highest yield during the 2019 dry season survey. IR 5154 was the variety used for all the simulations.

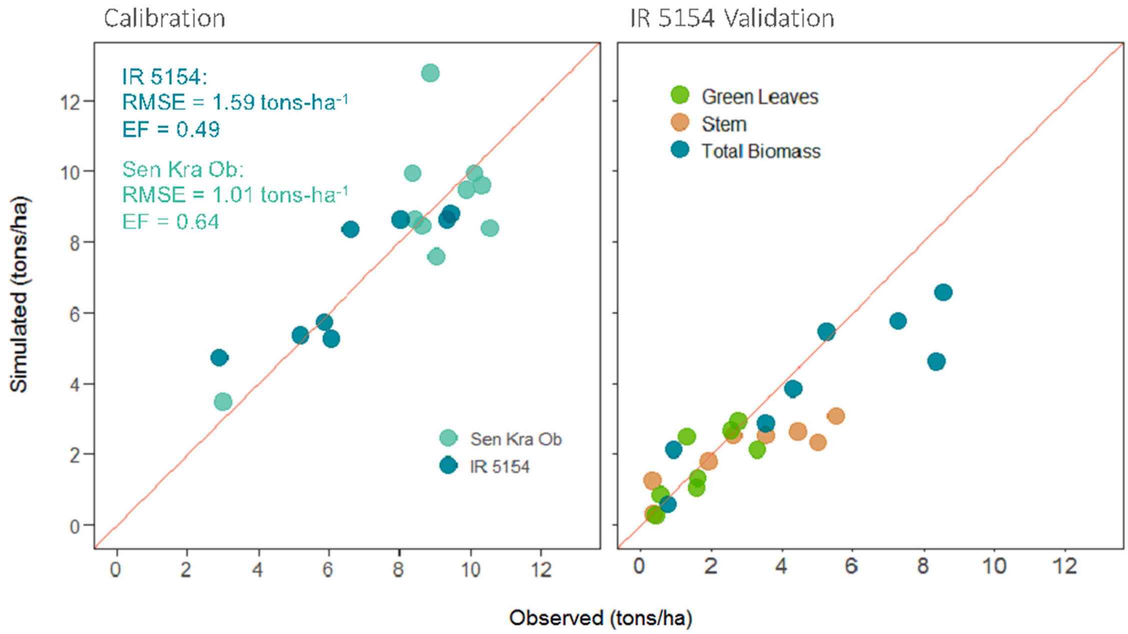

Fig. 5. Calibration and testing of IR 5154 and Sen Kra Ob varieties for ORYZA (v3) simulations. Calibration was based on the total biomass measured in the sample farms. Model testing was performed only for IR 5154. Partitioned and total biomass gathered during the 2019 dry season were used for model testing with corresponding values of the goodness-of-fit parameters listed on Table 5.

Table 5
Calculated RMSE, rRMSE, EF, and R^2 for plant biomass during parameterization and testing. Data used for calibration were measured during late vegetative to reproductive stage of crops planted in the dry season of 2018 while testing data were taken during the vegetative stage of 2019 dry season.

	Calibration				Model Testing			
	RMSE*	rRMSE	EF	R^2	RMSE*	rRMSE	EF	R^2
IR 5154								
Total biomass	1.59	18.0	0.49	0.48	1.66	34.0	0.67	0.79
Green leaves					0.64	36.4	0.56	0.52
Stem					1.51	51.0	0.35	0.73
Sen Kra Ob								
Total biomass	1.01	14.6	0.64	0.74				

*RMSE is in tons-ha^{-1}, rRMSE is in %

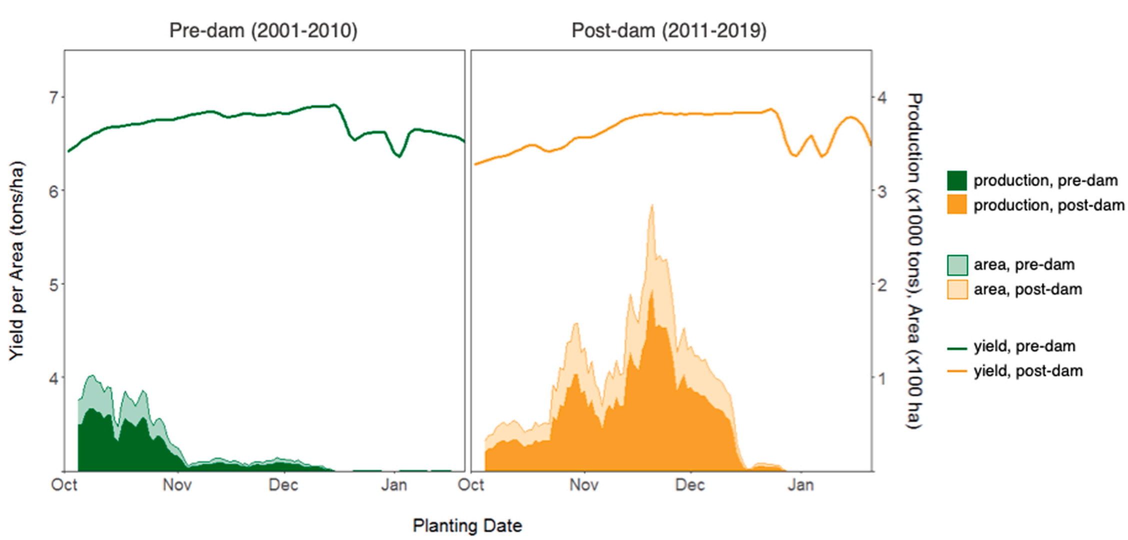

Fig. 6. Estimating the total production per day in Kampong Thom province by multiplying the attainable yield estimated by ORYZA (v3) and the area detected by PhenoRice at pre-dam (2001–2010) and post-dam (2011–2019) periods. IR 5154 variety was used for the simulations and agronomic inputs were based on the farm practices that produced the median yield during the site visit.

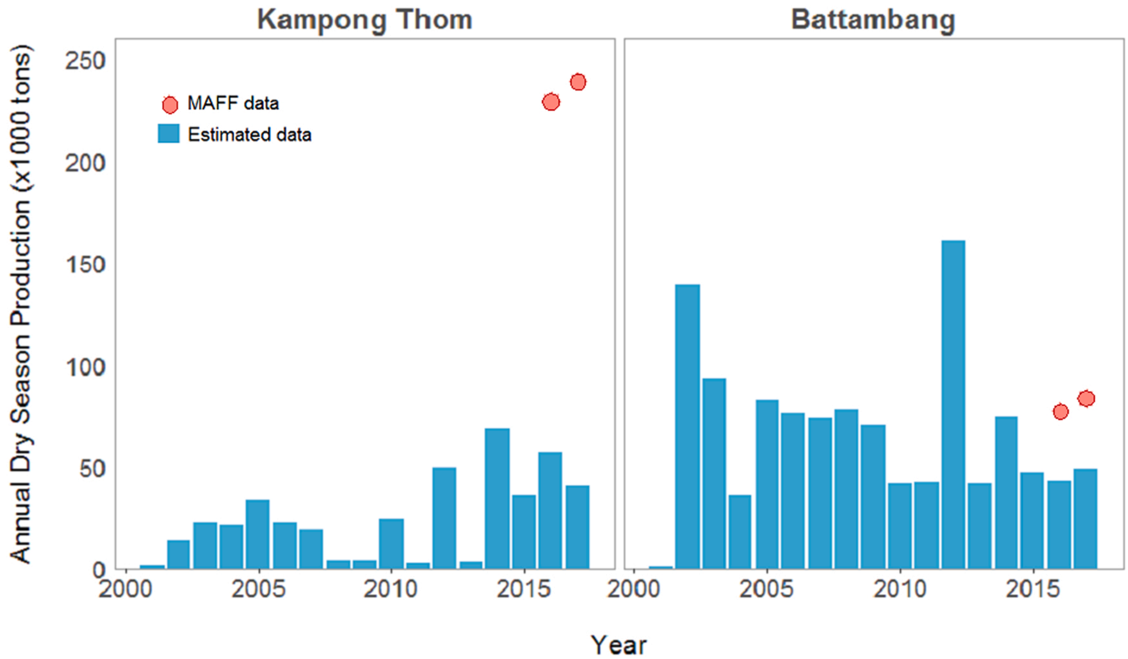

Fig. 7. Estimating the annual seasonal total production of Kampong Thom and Battambang provinces based on the attainable yield estimated by ORYZA (v3) and rice area detected by PhenoRice. Official data from MAFF in 2016 and 2017 are overlaid as individual data points to compare with estimated results.

The rate of yield increase with increasing SOC (Fig. 8B) were the same for all the treatments. Yield improvement by no more than 0.5 t-ha^{-1} was observed if the current SOC is increased by 50%. The relatively flatter slope of the line shown by the best farm practice indicated that not much value was added to their yield with increased SOC. On the other hand, decreasing the amount of SOC by 50% caused greater impact on yield, especially for medium- (0.50–0.58 t-ha^{-1}) and low-managed farms (0.46–0.50 t-ha^{-1}). Yield could decline in best-managed farms by 0.39 t-ha^{-1}, and increase of 0.20 t-ha^{-1} with decrease and increase of SOC by 50%, respectively.

3.4.3. Temperature increase

We simulated how change in temperature in Kampong Thom farms could affect the harvest yield with varying management practices, employing the same treatments used in SOC sensitivity analysis. The recorded average minimum and maximum daily temperature for these simulations were 23 and 35 °C, respectively. Results in Fig. 8C showed that abrupt declines in harvest yield occurred when temperature increased by more than 2 °C. Medium- and low-managed farms appeared to have less sensitivity to temperature decline of to up to 5 °C. Yield penalty as temperature rises were more observable in farms under

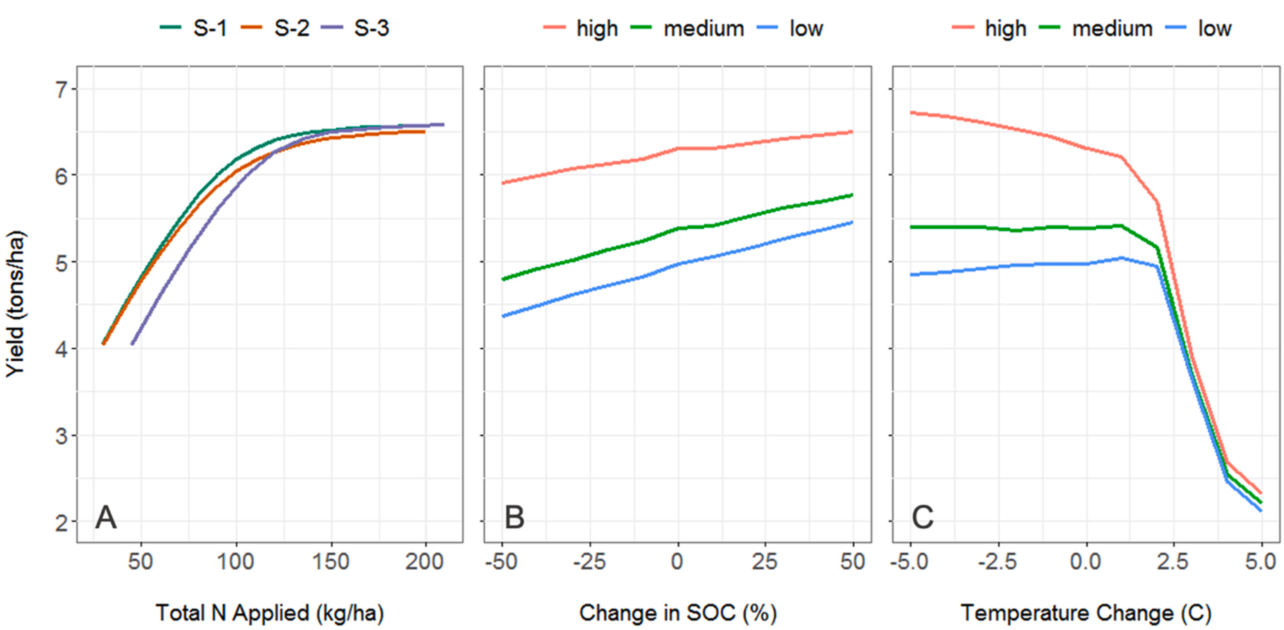

Fig. 8. Simulating yield response to A) N amount and timing of application, B) reduction and increase of soil organic carbon (SOC), and C) change in temperature. For N simulations (A), S-1 is applied at early tillering and panicle initiation (PI); S-2 at late tillering and booting; and S-3 at early tillering, late tillering, and PI. For SOC (B) and temperature simulations (C), the treatments were based on the agronomic practices observed in Kampong Thom. Low refers to the farm management practices that produced the lowest yield, medium for the median yield, and high for the management that obtained the highest yield during DS 2019. All simulations were executed in ORYZA (v3) using IR 5154 variety.

high agronomic management.

We then verified the possible yield response if the historical temperature was increased by 3 °C in Kampong Thom and Battambang (Fig. 9). This hypothetical increase in temperature was based on the predicted in average temperature increase in Cambodia by 2060 (World Bank, 2018). It was apparent in Fig. 9 that yield could decline by up to 4 tons-ha^{-1}, especially in late December to January at post-dam period in both provinces. Some dates that were no longer considered favorable for rice production, particularly late December to the first quarter of the year. Same management conditions were applied for both average and increased temperature simulations.

4. Discussion

4.1. Analysis on the changes in cropping patterns

Remote sensing complemented by crop model-based yield estimation fills the critical information gap when area-specific historical harvest and production and data are not available. Applying this method could also provide spatial and temporal perspective on the changes in cropping patterns that would aid land-use planners and policymakers in decisions related to resource management and food security.

In the case of Kampong Thom, expansion in cropping areas at post-dam period appeared to have spread both towards and away from the permanent lake (Fig. 4, A and B). This implies access to stored irrigation, which can be attributed to the gradual release of the flood waters accumulated during the monsoon season in more and newer hydropower dams. Recent findings by (Bonnema and Hossain, 2017) confirm that Lower Mekong Basin tributaries, which includes Tonle Sap, have already experienced extended dry season flooding from 2002 through 2015. Access to stored irrigation water allows rice farmers more flexibility to decide when to start their cropping. This was exemplified by the changes in planting dates detected by PhenoRice, shifting from October during pre-dam period to November and December during post-dam period (Fig. 3). The decreased correlation between the cultivated rice area and availability of surface water in Kampong Thom (Table 4) could indicate that farmers were less pressured in seizing the available floodwater before it drains for the rest of the dry season.

In contrast, if indeed the floodwater subsides sooner at the onset of dry season and the extent of the lake during the wet season has decreased during the post-dam period, the location of cultivation hotspots in Battambang in Fig. 4 (C and D) illustrate the early flood recession in the northern part of the lake (Fig. 4, C and D), whereby rice growers taking advantage of the available irrigation before it subsides. The geographic locations of Kampong Thom and Battambang relative to the Tonle Sap Lake (Fig. 1) demonstrate how rice production in the floodplains are dependent on the accessibility to floodwater. For instance, Kampong Thom gets flooded ahead of Battambang because of its proximity to the lake-river confluence. The latter drains water first and the former experiences longer inundation.

Without irrigation, planting needs to be done just before flood recedes. Our results found discernible associations with the availability of surface water (Table 4), the observed expansion in rice cultivation area (Table 3 and Fig. 3), and the spatio-temporal movement of rice production (Fig. 4). From a survey conducted by Joffre and de Silva (2015) from 2003 to 2013, they reported that dry season average irrigated area per household increased from 0 to 0.7 ha in Tonle Sap Lake's agricultural zones (Joffre and de Silva, 2015). If water supply is available, dry season rice production can be boosted further by reliable irrigation infrastructure (de Silva et al., 2014; Helmers, 1997; Veasna et al., 2014). Through the support of the Australian Centre for International Agricultural Research to CAVAC, 20 new irrigation schemes were built in Cambodia between 2010 and 2015 to divert water from rivers, making water more available year-round (ACIAR, 2015; GEF, 2019). Growing export demand, adoption of high-yielding varieties, agricultural mechanization, increased use of chemical fertilizers, and loan provisions for farmers also contribute to the improved productivity of dry season rice (Cramb, 2020; Cramb et al., 2020; Johnston et al., 2013; Liese et al., 2014; World Bank, 2015b), however these factors were not considered in our analysis. Nevertheless, current efforts from donor bodies to support the development and rehabilitation of irrigation canals and reservoirs (ADB, 2019; ACIAR, 2015; GEF, 2019) would keep Cambodia's momentum in increasing its dry season rice production.

We recognize that rice locations identified by PhenoRice were likely underestimated and may require thorough validation from high resolution satellite images and more in situ validation. Persistent cloud cover and precipitation were common sources of noise and Pixel Reliability indices were not sufficient to correct this error. It was stressed by the proponents of the algorithm (Busetto et al., 2019) that the main focus of PhenoRice was to estimate crop establishment based on phenological signals and has a known issue of underestimating rice areas. A two-year total production data (2016 and 2017) for Battambang and Kampong Thom was available from MAFF and were included in Fig. 6, but was insufficient as validation data points. The official MAFF reports (Fig. 7)

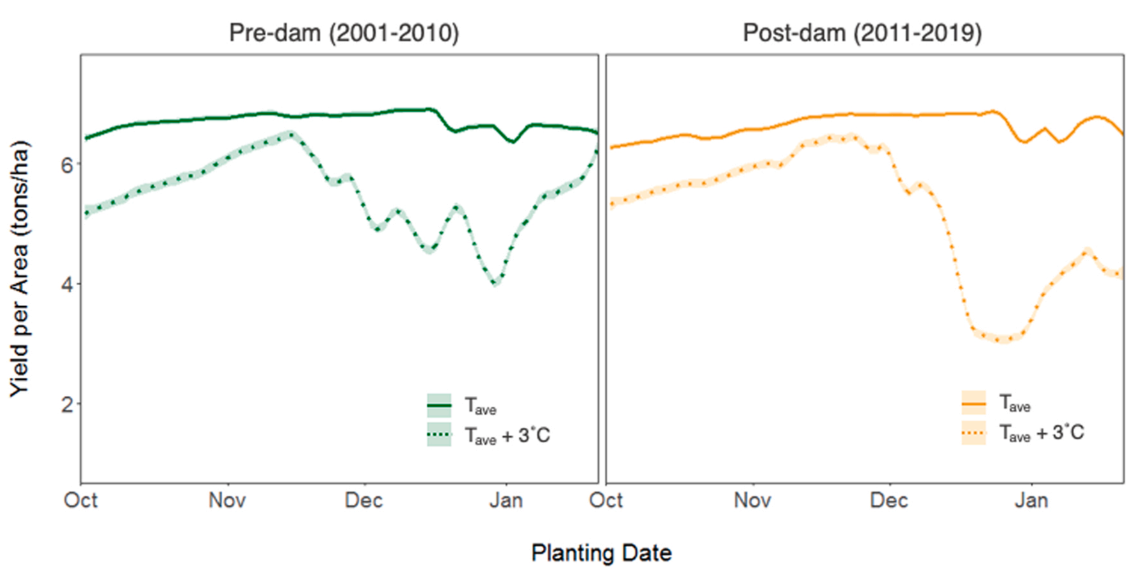

Fig. 9. ORYZA (v3) estimation of the attainable yield per establishment date in Kampong Thom at pre-dam and post-dam when temperature was increased by 3 °C from average temperature (T_{ave}). Simulations were conducted using IR 5154 and based from the farm practices that produced the median yield during the site visit.

showed that our estimate of rice production areas from PhenoRice likely underestimated the total rice production in Kampong Thom. Despite this limitation, the geographical and temporal planting patterns provide approximations of the difference between the rice production trends in the identified dam-periods.

4.2. Analysis on yield and production simulations

Area estimation by PhenoRice and yield simulations by ORYZA (v3) generated new information about the effects of various farm management practices, soil fertility, and increasing temperature to rice production and yield when historical provincial-level data was lacking. The capability of ORYZA (v3), a process-based crop model, to describe rice production in Kampong Thom and Battambang provinces was evaluated using actual farm measurements from 2018 and 2019 dry season cropping. Despite the limited sample points, the above-ground biomass data from IR 5154 and Sen Kra Ob provided acceptable goodness-of-fit during the calibration (Fig. 5, Table 5). Observed and simulated values were generally close to the 1:1 line therefore within allowable limits (Piñeiro et al., 2008). Model testing using the IR 5154 variety were generally satisfactory, with improved EF and R^2 especially for total biomass (Fig. 5 and Table 5). We put less priority in obtaining high model accuracy, rather, we aim to adequately provide yield trends through the crop model's ability to show responses from our variables of interest.

Yield and production simulations were focused on dry season cropping as dams in the Mekong River modulate water release downstream (Haddeland et al., 2006; Hecht et al., 2019; Kummu and Sarkkula, 2008), anticipating irrigation to be more available and opening up more farmlands for rice production. Historical production calculations were carried out only for Kampong Thom as our findings show that the effect of hydrology was more evident in this province. Succeeding yield response simulations were performed using IR 5154 since we were able to calibrate and test this variety in our crop model. Exploring the different farm management options in Fig. 8 assessed possible risks for farmers who tend to invest more time and inputs during the dry season (Cramb et al., 2020). Farmers can control more variables during the dry season compared to wet season, such as the delivery of water and fertilizer application that could result in better yield returns.

Limited nutrient availability is one of the major reasons for low productivity of rice in Cambodia (Kong et al., 2020). If reliable irrigation becomes more accessible for dry season cropping, farmers have better opportunity to maximize productivity and profitability from investing on chemical fertilizers. ORYZA (v3) results illustrated that once the maximum N threshold was reached, any additional N amount no longer contributed any considerable increase in yield (Fig. 8A). Simulations also showed that two-time application, one during vegetative and one during reproductive stage, was more efficient if the total applied N was less than 150 kg-ha^{-1}. During our site visits, most farmers interviewed in Kampong Thom reported applying less than this amount of fertilizer (Appendix C).

The model illustrated that when SOC was reduced by 50%, the yield penalty was greater than the potential yield gained if SOC was increased by 50% (Fig. 7B). Thus, highlighting the importance of the cyclic replenishment of soil nutrients in the Tonle Sap floodplains. Floodplain soil tend to be more fertile after monsoon flood recedes, when nutrient-rich sediments are brought ashore from the upstream (Arias et al., 2013). Natural soil enhancement provided by the flood pulse is not only sustainable, but it also benefits the farmers who can't afford commercial fertilizers. Fertilizer accounts for 21% of wet season and 37% of dry season input cost (Vuthy, 2014). In 2010, the World Bank reported that Cambodia is heavily reliant on importers for their fertilizer supply. Substandard and counterfeit products are also an issue because effective inspection procedures are not in place (Vuthy et al., 2014; World Bank, 2015b). This situation puts the farmers on the losing end, having to use fertilizer less than the recommended level because of the high price and the risk of benefiting less than what they paid for.

The farmers we interviewed related about instances when cropping was halted because of unreliable irrigation. Drier rainy season means lower water reserves, which was the case in our 2019 visit. Results of ORYZA (v3) simulations predicted that increasing the current average temperature by least 2 °C was critical and could cause significant yield decline (Fig. 8). The planting window where farmers can obtain the highest attainable yield may also shorten. In the future, sowing in late December to the first quarter of the year could be prone to higher yield loss (Fig. 9). Some farmers we interviewed do two cropping during the dry season. Their first sowing is in early October followed by second planting in late January to February. Based on our simulation results, warmer future scenario may not be favorable for late dry season production. Furthermore, with 3 °C temperature increase in Fig. 9, the drop in yield is most pronounced in December planting dates, which coincided with the increased planting area in the post-dam period. This could potentially mean that the gains in total rice production through improved access to water may be negated by an increase in temperature during the same period.

5. Conclusions

Dry season rice production in the Tonle Sap floodplains has intensified in recent years. Following the PhenoRice method, this study showed that most crop establishment activities shifted to November and December, areas of rice cultivation increased, and rice-growing locations became more dispersed. These changes coincided with the increase of dam developments in the Mekong River. As dams control the discharge of water downstream, irrigation becomes more accessible. This would give farmers more flexibility on the timing of crop establishment and could open more areas for rice cultivation. Although the ability of PhenoRice to detect rice areas needs further validation, the results of this study provided important observations to streamline the focus of future research studies. Accuracy in detecting rice area can be improved by using satellite images with higher temporal and/or spatial resolution. Thorough ground-truthing is also recommended.

Various simulation scenarios were explored using ORYZA (v3) to predict yield responses to farm management practices, soil fertility, and increasing temperature. Testing different N management regimes, we determined the optimum N required and the best timing of application to get the attainable yield of the sample rice variety. The model also estimated the yield loss/increase if the present soil organic carbon concentrations are reduced/increased by 50%. We identified that an increase by at least 2 °C from the current average temperature could lead to drastic yield loss, shorten the ideal planting window for sowing, and prevent late or second cropping in future warmer dry seasons. Examining these changes in rice production and drivers of yield are critical in forecasting and decision-making related to food security and water resource management in the Lower Mekong Region. Providing insights on when and where to cultivate rice would provide information to policymakers to set guidelines that will be equitable to local communities that depend upon the ecosystem services of the Tonle Sap Lake.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This paper is based upon work supported by the National Science Foundation under Grant No. 1740042 through the Innovations at the Nexus of Food, Energy and Water Systems Program. Special thanks to Chhay Kry, Hong Norm, Soma Voeun, and Chhun Sokunroth for their valuable assistance during our field work in Cambodia. This research would not have been possible without the information provided by the

participating farmers in Kampong Thom and Battambang provinces.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2021.107183.

References

Arias, M.E., Cochrane, T.A., Norton, D., Killeen, T.J., Khon, P., 2013. The flood pulse as the underlying driver of vegetation in the largest wetland and fishery of the Mekong Basin. Ambio 42. https://doi.org/10.1007/s13280-013-0424-4.

Arias, M.E., Cochrane, T.A., Piman, T., Kummu, M., Caruso, B.S., Killeen, T.J., 2012. Quantifying changes in flooding and habitats in the Tonle Sap Lake (Cambodia) caused by water infrastructure development and climate change in the Mekong Basin. J. Environ. Manag. 112. https://doi.org/10.1016/j.jenvman.2012.07.003.

Asian Development Bank (ADB), 2019. Irrigated Agriculture Improvement Project: Report and Recommendation of the President [WWW Document]. URL 〈https://www.adb.org/projects/documents/cam-51159–002-rrp〉 (accessed 23 June 2020).

Australian Centre for International Agricultural Research (ACIAR), 2015. Cambodia Agricultural Value Chain program (CAVAC) Phase II [WWW Document]. URL 〈http://exchange.growasia.org/system/files/investment-design-cambodia-agricultural-value-chain-program-phase-ii.pdf〉 (accessed 23 June 2020).

Belder, P., Bouman, B.A.M., Spiertz, J.H.J., Peng, S., Castañeda, A.R., Visperas, R.M., 2005. Crop performance, nitrogen and water use in flooded and aerobic rice. Plant Soil 273. https://doi.org/10.1007/s11104-004-7401-4.

Beveridge, C., Hossain, F., Bonnema, M., 2020. Estimating impacts of dam development and landscape changes on suspended sediment concentrations in the Mekong River Basin's 3S tributaries. J. Hydrol. Eng. 25. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001949.

Bivand R., Keitt T., Rowlingson B., Pebesma E., Sumner M., Hijmans R., Baston D., Rouault E., Warmerdam F., Ooms J., Colin Rundel, 2021. rgdal: Bindings for the "Geospatial" Data Abstraction Library.

Boling, A.A., Bouman, B.A.M., Tuong, T.P., Murty, M.V.R., Jatmiko, S.Y., 2007. Modelling the effect of groundwater depth on yield-increasing interventions in rainfed lowland rice in Central Java, Indonesia. Agric. Syst. 92. https://doi.org/10.1016/j.agsy.2006.05.003.

Bonnema, M., Hossain, F., 2017. Inferring reservoir operating patterns across the Mekong Basin using only space observations. Water Resour. Res. 53. https://doi.org/10.1002/2016WR019978.

Boote, K.J., Jones, J.W., Pickering, N.B., 1996. Potential uses and limitations of crop models. Agron. J. 88. https://doi.org/10.2134/agronj1996.00021962008800050005x.

Boschetti, M., Busetto, L., Manfron, G., Laborte, A., Asilo, S., Pazhanivelan, S., Nelson, A., 2017. PhenoRice: a method for automatic extraction of spatio-temporal information on rice crops using satellite data time series. Remote Sens. Environ. 194. https://doi.org/10.1016/j.rse.2017.03.029.

Boschetti, M., Nutini, F., Manfron, G., Brivio, P.A., Nelson, A., 2014. Comparative analysis of normalised difference spectral indices derived from MODIS for detecting surface water in flooded rice cropping systems. PLoS One 9. https://doi.org/10.1371/journal.pone.0088741.

Bouman B., Kropff M., Wopereis M., ten Berge H., van Laar H., 2001. ORYZA2000: modeling lowland rice. International Rice Research Institute (IRRI), Los Baños, Philippines.

Busetto, L., Ranghetti, L., 2016. MODIStsp: an R package for automatic preprocessing of MODIS Land Products time series. Comput. Geosci. 97. https://doi.org/10.1016/j.cageo.2016.08.020.

Busetto, L., Zwart, S.J., Boschetti, M., 2019. Analysing spatial–temporal changes in rice cultivation practices in the Senegal River Valley using MODIS time-series and the PhenoRice algorithm. Int. J. Appl. Earth Obs. Geoinf. 75, 15–28. https://doi.org/10.1016/j.jag.2018.09.016.

Chen, J., Jönsson, P., Tamura, M., Gu, Z., Matsushita, B., Eklundh, L., 2004. A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky-Golay filter. Remote Sens. Environ. 91, 332–344. https://doi.org/10.1016/j.rse.2004.03.014.

Costantini, A., 1995. Soil sampling bulk density in the coastal lowlands of south-east queensland. Aust. J. Soil Res. 33, 11–18. https://doi.org/10.1071/SR9950011.

Cramb, R. (Ed.), 2020. White Gold: The Commercialisation of Rice Farming in the Lower Mekong Basin. Springer Singapore, Singapore.

Cramb, R., Sareth, C., Vuthy, T., 2020. The commercialisation of rice farming in Cambodia. In: Cramb, R. (Ed.), White Gold: The Commercialisation of Rice Farming in the Lower Mekong Basin. Springer Singapore, Singapore, pp. 227–245. https://doi.org/10.1007/978-981-15-0998-8_11.

Daly, K., Ahmad, S.K., Bonnema, M., Beveridge, C., Hossain, F., Nijssen, B., Holtgrieve, G., 2020. Recent warming of Tonle Sap Lake, Cambodia: implications for one of the world's most productive inland fisheries. Lakes Reserv. Res. Manag. 25. https://doi.org/10.1111/lre.12317.

de Silva, S., Johnston, R., Sellamuttu, S.S., 2014. Agriculture, Irrigation and Poverty Reduction In Cambodia: Policy Narratives and Ground Realities Compared [WWW Document]. URL 〈http://pubs.iclarm.net/resource_centre/AAS-2014–13.pdf〉 (accessed 27 June 2020).

Pebesma, Edzer, 2018. Simple features for R: standardized support for spatial vector data. R. J. 10. https://doi.org/10.32614/RJ-2018-009.

Eyler, B., Weatherby, C., 2019. Letters from the Mekong: Toward A Sustainable Water-Energy Food Future in Cambodia. Washington, DC.

Food and Agriculture Organization (FAO), 2015. Cambodia country fact sheet on food and agriculture policy trends [WWW Document]. URL 〈http://www.fao.org/3/i3761e/i3761e.pdf〉 (accessed 15 June 2020).

Ghani, A., Dexter, M., Perrott, K.W., 2003. Hot-water extractable carbon in soils: a sensitive measurement for determining impacts of fertilisation, grazing and cultivation. Soil Biol. Biochem. 35, 1231–1243. https://doi.org/10.1016/S0038-0717(03)00186-X.

Global Environment Facility (GEF), 2019. Promoting Climate-Resilient Livelihoods in Rice-Based Communities in the Tonle Sap Region [WWW Document]. URL 〈https://www.thegef.org/sites/default/files/web-documents/10177_LDCF_Cambodia_PIF.pdf〉 (accessed 19 June 2020).

Greweling, T., Peech, M., 1960. Chemical Soil Test. Cornell Univ. Agric. Exp. Stn.

Haddeland, I., Lettenmaier, D.P., Skaugen, T., 2006. Effects of irrigation on the water and energy balances of the Colorado and Mekong river basins. J. Hydrol. 324, 210–223. https://doi.org/10.1016/j.jhydrol.2005.09.028.

Hecht, J.S., Lacombe, G., Arias, M.E., Dang, T.D., Piman, T., 2019. Hydropower dams of the Mekong River basin: a review of their hydrological impacts. J. Hydrol. 568, 285–300. https://doi.org/10.1016/j.jhydrol.2018.10.045.

Helmers, K., 1997. Rice in the Cambodian economy: past and present. In: Nesbitt, H.J. (Ed.), Rice Production in Cambodia. International Rice Research Institute (IRRI), Manila, Philippines, pp. 1–14.

Hijmans, R.J., Van Etten, J., 2012. raster: Geographic Data Analysis and Modeling.

Hortle, K.G., Lieng, S., Valbo-Jorgensen, J., 2004. An introduction to Cambodia's inland fisheries [WWW Document]. URL 〈https://www.mrcmekong.org/assets/Publications/report-management-develop/Mek-Dev-No4-Mekong-Fisheries-Cambodia-Eng.pdf〉 (accessed 4 September 2019).

Huete, A., Justice, C., Liu, H., 1994. Development of vegetation and soil indices for MODIS-EOS. Remote Sens. Environ. 49, 224–234. https://doi.org/10.1016/0034-4257(94)90018-3.

Huluka, G., Miller, R., 2014. Particle size determination by hydrometer method. Soil Test Methods from the Southeastern United States. South. Coop. Ser. Bull.

Jackson, M.L., 1959. Soil chemical analysis. J. Plant Nutr. Soil Sci. 85. https://doi.org/10.1002/jpln.19590850311.

Joffre, O.M., de Silva, S., 2015. Community Water Access, Availability and Management Survey in the Tonle Sap Region [WWW Document]. URL 〈https://aquadocs.org/bitstream/handle/1834/32480/AAS-2015–04.pdf?sequence=1&isAllowed=y〉 (accessed 14 September 2019).

Johnston, R., Roberts, M., Try, T., De Silva, S., 2013. Groundwater for Irrigation in Cambodia [WWW Document]. URL 〈http://www.iwmi.cgiar.org/Publications/issue_briefs/cambodia/issue_brief_03-groundwater_for_irrigation_in_cambodia.pdf〉 (accessed 22 June 2020).

Kondolf, G.M., Rubin, Z.K., Minear, J.T., 2014. Dams on the Mekong: cumulative sediment starvation. Water Resour. Res. 50. https://doi.org/10.1002/2013WR014651.

Kong, K., Hin, S., Seng, V., Ismail, A.M., Vergara, G., Choi, I.-R., Ehara, H., Kato, Y., 2020. Importance of phosphorus and potassium in soil-specific nutrient management for wet-season rice in Cambodia. Exp. Agric. 56. https://doi.org/10.1017/S0014479719000309.

Kummu, M., Sarkkula, J., 2008. Impact of the Mekong river flow alteration on the Tonle Sap flood pulse. Ambio 37, 185–192. https://doi.org/10.1579/0044-7447(2008)37[185:IOTMRF]2.0.CO;2.

Lamberts, D., 2006. The Tonle Sap lake as a productive ecosystem. Int. J. Water Resour. Dev. 22. https://doi.org/10.1080/07900620500482592.

Li, T., Angeles, O., Marcaida, M., Manalo, E., Manalili, M.P., Radanielson, A., Mohanty, S., 2017. From ORYZA2000 to ORYZA (v3): an improved simulation model for rice in drought and nitrogen-deficient environments. Agric. . Meteorol. 237–238, 246–256. https://doi.org/10.1016/j.agrformet.2017.02.025.

Li, T., Angeles, O., Radanielson, A., Marcaida, M., Manalo, E., 2015. Drought stress impacts of climate change on rainfed rice in South Asia. Clim. Change 133. https://doi.org/10.1007/s10584-015-1487-y.

Liese, B., Isvilanonda, S., Ngoc, L.N., Pananurak, P., Pech, R., Shwe, T., Sombounkhanh, K., Möllmann, T., Zimmer, Y., 2014. Economics of Southeast Asian Rice Production [WWW Document]. URL 〈http://www.agribenchmark.org/fileadmin/Dateiablage/B-Cash-Crop/Reports/Report-2014–1-rice-FAO.pdf〉 (accessed 19 June 2019).

Matsui, S., Keskinen, M., Sokhem, P., Nakamura, M., 2006. Tonle SapExperience and Lessons Learned Brief [WWW Document]. URL 〈https://iwlearn.net/documents/5987〉 (accessed 4 September 2019).

Mekong River Commission, 2010. Impacts on the Tonle Sap Ecosystem [WWW Document]. Mekong River Comm. URL 〈http://www.probeinternational.org/Impacts-on-the-Tonle-Sap-Ecosystem%28June-10%29.pdf〉 (accessed 29 July 2020).

Ministry of Agriculture, Forestry, and F. (MAFF), 2018. Annual Report for Agriculture Forestry and Fisheries 2017–2018 and Directions 2018–2019 [WWW Document]. URL 〈https://www.oads.or.kr/upload_file/bbs/56–1.MAFF-2017–2018〉 (EN)-Final-Binder.pdf (accessed 29 March 2019).

Ministry of Agriculture, Forestry, and F. (MAFF), 2017. Annual Report for Agriculture Forestry and Fisheries 2016–2017 and Directions 2017–2018 [WWW Document]. URL 〈https://www.oads.or.kr/upload_file/bbs/56–1.MAFF-2017–2018〉 (EN)-Final-Binder.pdf (accessed 20 June 2020).

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50, 885–900. https://doi.org/10.13031/2013.23153.

NASA Goddard Space Flight Center, Ocean Ecology Laboratory, O.B.P.G, 2014a. MODIS-Terra Ocean Color Data [WWW Document]. URL ⟨https://oceancolor.gsfc.nasa.gov/data/terra/⟩ (accessed 14 September 2019).

NASA Goddard Space Flight Center, Ocean Ecology Laboratory, O.B.P.G, 2014b. MODIS-Aqua Ocean Color Data [WWW Document]. URL ⟨https://oceancolor.gsfc.nasa.gov/data/aqua/⟩ (accessed 14 September 2019).

Nesbitt, H.J. (Ed.), 1997. Rice production in Cambodia. International Rice Research Institute (IRRI), Manila, Philippines.

Nguyen, Y.T.B., Kamoshita, A., Araki, Y., Ouk, M., 2011. Farmers' management practices and grain yield of rice in response to different water environments in Kamping Puoy Irrigation Rehabilitation Area in Northwest Cambodia. Plant Prod. Sci. 14, 377–390. https://doi.org/10.1626/pps.14.377.

Piñeiro, G., Perelman, S., Guerschman, J.P., Paruelo, J.M., 2008. How to evaluate models: observed vs. predicted or predicted vs. observed? Ecol. Modell. 216, 316–322. https://doi.org/10.1016/j.ecolmodel.2008.05.006.

Pokhrel, Y., Burbano, M., Roush, J., Kang, H., Sridhar, V., Hyndman, D., 2018a. A review of the integrated effects of changing climate, land use, and dams on Mekong River hydrology. Water 10. https://doi.org/10.3390/w10030266.

Pokhrel, Y., Shin, S., Lin, Z., Yamazaki, D., Qi, J., 2018b. Potential disruption of flood dynamics in the lower Mekong river basin due to upstream flow regulation. Sci. Rep. 8. https://doi.org/10.1038/s41598-018-35823-4.

R Core Team, 2020. R: A Language and Environment for Statistical Computing.

Radanielson, A.M., Gaydon, D.S., Li, T., Angeles, O., Roth, C.H., 2018. Modeling salinity effect on rice growth and grain yield with ORYZA v3 and APSIM-Oryza. Eur. J. Agron. 100, 44–55. https://doi.org/10.1016/j.eja.2018.01.015.

Ricepedia, 2018. Cambodia [WWW Document]. URL ⟨https://ricepedia.org/cambodia⟩ (accessed 28 July 2020).

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., Jones, J.W., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proc. Natl. Acad. Sci. USA 111. https://doi.org/10.1073/pnas.1222463110.

Royal Government of Cambodia, 2010. Policy Paper On The Promotion of Paddy Production and Rice Export. Phnom Penh.

Sabo, J.L., Ruhi, A., Holtgrieve, G.W., Elliott, V., Arias, M.E., Ngor, P.B., Räsänen, T.A., Nam, S., 2017. Designing river flows to improve food security futures in the Lower Mekong Basin. Science 358. https://doi.org/10.1126/science.aao1053.

Sadras, V.O., Cassman, K.G., Grassini, P., Hall, A.J., Bastiaanssen, W.G.M., Laborte, A.G., Milne, A.E., Sileshi, G., Steduto, P., 2015. Yield Gap Analysis of Field Crops. Methods and Case Studies.

Saxton, K.E., Rawls, W.J., 2006. Soil water characteristic estimates by texture and organic matter for hydrologic solutions. Soil Sci. Soc. Am. J. 70. https://doi.org/10.2136/sssaj2005.0117.

Setiyono, T., Quicho, E., Gatti, L., Campos-Taberner, M., Busetto, L., Collivignarelli, F., García-Haro, F., Boschetti, M., Khan, N., Holecz, F., 2018. Spatial rice yield estimation based on MODIS and sentinel-1 SAR data and ORYZA crop growth model. Remote Sens. 10. https://doi.org/10.3390/rs10020293.

Siek, D., Xu, S.W., Wyu, Ahmed, A.-G., 2017. Impact of livestock scale on rice production in Battambang of Cambodia. IOP Conf. Ser.: Earth Environ. Sci. 86, 012019 https://doi.org/10.1088/1755-1315/86/1/012019.

Sithirith, M., 2017. Water governance in cambodia: from centralized water governance to farmer water user community. Resources 6. https://doi.org/10.3390/resources6030044.

Smith, D.J., Hornbuckle, J.W., 2013. A review on rice productivity in Cambodia and water use measurement using direct and indirect methods on a dry season rice crop [WWW Document]. URL ⟨https://publications.csiro.au/rpr/download?pid=csiro:EP1310226&dsid=DS6⟩ (accessed 29 March 2020).

Sopheap, E., Setka, S., Mithona, A., Seiha, T., Thong, K., Saio, K., 2018. Quality and safety of Cambodian rice. Food Sci. Technol. Res. 24, 829–838. https://doi.org/10.3136/fstr.24.829.

Stevens, A., Ramirez-Lopez, L., 2020. An introduction to the prospectr package.

Stone, R., 2016. Dam-building threatens Mekong fisheries. Science 354. https://doi.org/10.1126/science.354.6316.1084.

Sudhir-Yadav, S., Li, T., Humphreys, E., Gill, G., Kukal, S.S., 2011. Evaluation and application of ORYZA2000 for irrigation scheduling of puddled transplanted rice in north west India. Field Crop. Res. 122, 104–117. https://doi.org/10.1016/j.fcr.2011.03.004.

Thoeun, H.C., 2015. Observed and projected changes in temperature and rainfall in Cambodia. Weather Clim. Extrem. 7, 61–71. https://doi.org/10.1016/j.wace.2015.02.001.

USDA, 2010. CAMBODIA: Future Growth Rate of Rice Production Uncertain [WWW Document]. URL ⟨https://ipad.fas.usda.gov/highlights/2010/01/cambodia/⟩ (accessed 19 June 2020).

Veasna T., Bunna S., Roat M.P., Vanndy L., Sinat P., Vang S., Chantha O., Viraday N., Nareth M., Kanthel P., Tara T., Veasna HE P., Hing U., Collins M., Hornbuckle J., Quayle W., Smith D., Zandona R., 2014. Improved irrigation water management to increase rice productivity in Cambodia, in: A Policy Dialogue on Rice Futures: Rice-Based Farming Systems Research in the Mekong Region. pp. 92–102.

Vuthy, T., 2014. Policy challenges for Cambodia's agricultural development and food security—a review of the rice sector. In: Robins, L. (Ed.), A Policy Dialogue on Rice Futures: Rice Based Farming Systems Research in the Mekong Region. Australian Centre for International Agricultural Research (ACIAR), Phnom Penh, pp. 152–158.

Vuthy, T., Pirom, K., Dary, P., 2014. Development of the Fertiliser Industry in Cambodia: Structure of the Market, Challenges in the Demand and Supply Sides, and the Way Forward Initiative on The Role of Fertilisers and Seeds in Transforming Agriculture in Asia.

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T., Miller, E., Bache, S., Müller, K., Ooms, J., Robinson, D., Seidel, D., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., Yutani, H., 2019. Welcome to the Tidyverse. J. Open Source Softw. 4. https://doi.org/10.21105/joss.01686.

World Bank, 2018. Climate change knowledge portal [WWW Document]. ⟨https://climateknowledgeportal.worldbank.org/country/cambodia⟩.

World Bank, 2015a. Cambodia: The Agriculture, Irrigation, and Rural Roads Sectors – Public Expenditure Review [WWW Document]. URL ⟨http://hdl.handle.net/10986/22509⟩.

World Bank, 2015b. Cambodia Quality Assessment Report. Rapid Appraisal of Fertility Quality in Cambodia [WWW Document]. URL ⟨https://openknowledge.worldbank.org/bitstream/handle/10986/22539/Cambodia000Qua00quality0in0Cambodia.pdf?sequence=1&isAllowed=y⟩ (accessed 19 July 2020).

World Health Organization (WHO), 2016. Climate and Health Country Profile-2015: Cambodia [WWW Document]. URL ⟨https://www.who.int/publications/i/item/health-and-climate-change-country-profile-2015-cambodia⟩ (accessed 27 June 2010).

Zambrano-Bigiarini, M., 2020. hydroGOF: Goodness-of-fit functions for comparison of simulated and observed hydrological time serie.

Asian Development Bank, 2012. Climate Resilient Rice Commercialization Sector Development Program [WWW Document]. URL https://www.adb.org/sites/default/files/linked-documents/44321-013-cam-oth-03.pdf (accessed 23 June 2020).