Rice Production in Tonle Sap Floodplains in Response to Anthropogenic Changes in Hydrology, Climate, and Agronomic Practices

Manuel P. Marcaida III

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Soo-Hyung Kim

Faisal Hossain

Rebecca Neumann

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Abstract

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Manuel P. Marcaida III

Chair of the Supervisory Committee:
Soo-Hyung Kim
Environmental and Forest Sciences

Rice is the most important agricultural commodity in Cambodia as food and source of livelihood. Majority of rice production happens around the Tonle Sap floodplains sustained by the sediment-rich flood from the Mekong River. With the increased construction of hydropower dams upstream, the natural flow of water, organic materials, and fish species delivered to the Tonle Sap Lake is altered. While these changes open up more areas for rice cultivation especially during the dry season, the quality of the sediments is expected to decline. Moreover, drought is becoming a frequent occurrence and temperature is increasing. This study examined how the rice cultivation in the Tonle Sap floodplains is impacted by the hydrological changes, climate, and agronomic practices. Specifically, we 1) assessed the impacts of the increasing presence of dams on the timing and location of rice cropping, and 2) tested and applied an ecophysiological crop model to simulate the effect of changes in hydrology, agronomic practices, and increasing temperature on rice production in Tonle Sap floodplains.

Spatio-temporal effect of dams in rice production was identified following the PhenoRice algorithm, focusing on two rice-growing provinces, Kampong Thom and Battambang, using time-series satellite images from 2001 to 2019. Yield simulations to determine the effect of hydrology, agronomic practices, and increasing temperatures were executed in ORYZA (v3) Rice Model, validated by actual field measurements and personal interviews with farmers. The model estimated the total production per planting time and yield responses to varying soil organic carbon content, N application, and temperature.

PhenoRice results showed that the rice cultivation increased with lake extent during dry season. In addition, location and the timing of crop establishment were adjusted depending on the availability of floodwater. The identified rice areas from PhenorRice were used to estimate the total production in ORYZA (v3), as influenced by changing climate and hydrology. The rice model predicted that the yield penalty with decreasing soil organic carbon was greater than the yield gained from increasing it. We determined the optimum N required and efficient timing of applications to get the maximum attainable yield. The model also showed that increasing temperature decreases yield but drastic loss occurred when temperature was increased by more than 2 °C. This study provides information on how hydrology, climate, and agronomic practices impact rice production in Cambodia that are vital for making important decisions related to water management and food security in the Lower Mekong Region.

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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. It is the most important agricultural crop in Cambodia. About 85% of the country's croplands is cultivated for rice (Siek, et al., 2017), which speaks volumes for an economy that is largely reliant on its agricultural sector. In recent years, rice production has increased at a rate of 0.1 t-ha$_{-1}$ from year 2000 to 2014 (RicePedia, 2018) with the introduction of new hybrid varieties and expansion of dry season paddy rice. The Global Agricultural Information Center reported an increase in dry season yield from 3.4 to 3.9 t-ha$_{-1}$ (0.037 t-year$_{-1}$) and 2.1 to 2.6 t-ha$_{-1}$ (0.039 t-year$_{-1}$) in wet season from 2007 to 2019 (GAIN, 2018; GAIN, 2019; GAIN, 2020). Cambodian rice is also gaining recognition for its high eating quality. The goal of the Ministry of Agriculture and Forestry and Fisheries (MAFF) is to transform Cambodia into a major rice exporter in the global market. Despite these developments, Cambodia still lags behind Thailand and Vietnam, its top rice-producing neighbors that also enjoy the irrigation benefits from the rich Mekong River ecosystem.

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% is used for rice production. Tonle Sap 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. 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. 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. About 500,000 tons of fish are produced each year that provides 75% of dietary proteins of Cambodian people (Eyler, 2019). Other areas are occupied by flooded forests and grasslands that provide habitats to rich flora and fauna.

This natural cycle of biota exchange between Tonle Sap and Mekong River is threatened by the increase in hydropower dams along the Mekong River in recent decades. While dams and hydroelectric power plants are built to improve energy production in the Lower Mekong by providing rural areas access to less expensive electricity, it also impacts the flow of water between the river and its tributaries affecting the livelihood of the same local communities. Furthermore, the connectivity of the floodplains to the river is already reduced by 31% (Eyler and Weatherby, 2019), altering the timing and intensity of flood pulse. The extent of the lake during the dry season (October to March) is expected to increase and the volume of water during the monsoon season is expected to decrease. These hydrological changes influence planting time and opens up more lands for rice farming, which primarily depend on accessibility to the lake and its tributaries for irrigation.

Rice is a water-dependent crop. To produce a kilogram of rice requires an average of 2,500 liters of water (Bouman, 2009), which can either be supplied through rainfall, irrigation, or combination of both. In Cambodia, rice is predominantly grown in the wet season contributing 80% of the total production, completely dependent on rainfall and floodwater (USDA, 2010).

Based on the availability of water in the lake, wet season is further subdivided into rainfed wet-season where rice are sown at the outer edges of the floodplains and land is inundated for only one month or less annually; the flooded rice where farms are inundated for 1 to 5 months; and the recession rice, where farms take advantage of the retained floodwater. During the wet season, farmers tend to invest less on inputs and management due to variability of rainfall and unpredictable flooding.

Dry season contributes to only 20% of the cultivated rice area but produces at least 50% greater yield per paddy area than wet season rice (Smith and Hornbuckle, 2013). This is attributed to higher solar radiation during crop growth, farmers' preference of sowing modern rice varieties, reduced risk of prolonged submergence due to flooding, and better irrigation control. Several irrigation options are available such as reservoirs, river diversion using canals, and groundwater extraction that farmers are motivated to invest more on inputs such as commercial fertilizers. There is a strong incentive to apply fertilizers during the dry season because the risk of getting drained by unpredictable flood and rainfall is much less. As the upstream dams make irrigation more available during the dry season, there is even greater opportunity to produce more rice and potentially boost Cambodia's export market.

It is important to examine how Tonle Sap's hydrology has changed over the years and its effect on rice cropping patterns. Earth observation data acquired from satellite image can provide this information. Rice production can be identified by detecting agronomic flooding during the start of the cropping season and subsequent changes in 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 through identifying signals of crop establishment and key phases of crop development. On the other hand, effects of climate and agronomic variables that contribute to rice yield and production can be explained using crop modeling. The ORYZA (v3) Rice Model (Bouman, 2001; Li et al., 2017) was specifically designed to simulate rice growth and development. It has the ability to estimate the effect of climate, soil carbon and nitrogen dynamics, irrigation, and farm management practices to harvest yield at varying rice production environments.

Comprehensive water management and forecasting of changes in rice production and yield in relation to the movement of water inundation in the Tonle Sap ecosystem is critical in making important decisions on food security in the Lower Mekong Region. For instance, with the undeniable presence of dams, providing guidelines on how much and when to discharge water will aid in ensuring irrigation demands are met in the cropping areas.

This study examined how rice productivity in the Tonle Sap floodplains is impacted by the continuing construction of hydropower dams in the upstream Mekong River, climate change, farm management practices, and field abiotic conditions. Using remote sensing and crop modeling, our research was designed to accomplish the following objectives: 1) to detect the changes in timing and location of crop establishment before and after the surge of dam installations following the PhenoRice method and 2) to test and apply the ORYZA (v3) Rice Model in simulating the effect of changes in hydrology, increasing temperature, and agronomic practices to rice production and yield.

2 METHODOLOGY

2.1 SPATIO-TEMPORAL CHANGES IN CROP ESTABLISHMENT

As the extent of the permanent lake increases during the dry season (DS) and the intensity of flooding decreases during the wet season (WS), changes in planting time and location can be expected depending on the availability of irrigation. We aim to capture the changes in timing and location of rice production during the DS and WS from 2001 to 2019 using remote sensing, following the PhenoRice method formulated by Boschetti et al. (2017). Based on the study conducted by Hecht, et al. (2019) dam constructions dramatically increased from 2010 and beyond, therefore we designated 2001 to 2010 as "pre-dam" and 2011 to 2019 as "post-dam", which we refer to as "dam-periods". Rice are grown in WS from May to September, and in DS from October to April.

2.1.1 *STUDY SITES*

This study focuses on Kampong Thom and Battambang, two of the major rice-producing provinces in Cambodia (Fig. 1). In 2017, MAFF reported that Battambang contributed 11.0% (1.15 million tons) and Kampong Thom shared 7.9% (0.80 million tons) to the country's total rice production. In the same year, Kampong Thom accounted for 8.09% and 9.81% of the total WS and DS area, respectively. On the other hand, Battambang contributed 12.55% of Cambodia's total WS cultivated area and 3.74% of total DS area (MAFF, 2018). Direct-seeding by manual broadcasting is the common sowing practice in both seasons. Rice growers in these provinces rely on rainfall and lake water for rice production during the WS and through irrigation systems such as canals and reservoirs that distributes the remaining water from Tonle Sap and its tributaries during the DS. Kampong Thom is located in the central part of Cambodia and much of its locality lies in the southeastern part of the Tonle Sap floodplain. Its location is close to the confluence that connects the lake to the Mekong River exposing it to early and prolonged inundation. Rice is commonly planted in the latter part of the WS to early dry season, which is around September to November. Battambang is situated in the northwestern part of Cambodia and by the northern end of the Tonle Sap Lake. It has one of the largest irrigated paddy rice areas in the country and the top producer of WS rice, which can be attributed to the water management system provided by Kamping Pouy Reservoir on the western side of the province. The locations of these two provinces provide a perspective on the cropping pattern with respect to the movement of flooding from the start of the monsoon until the flood recedes in DS. Kampong Thom experiences early and longer flooding while Battambang experiences late inundation and early flood recession.

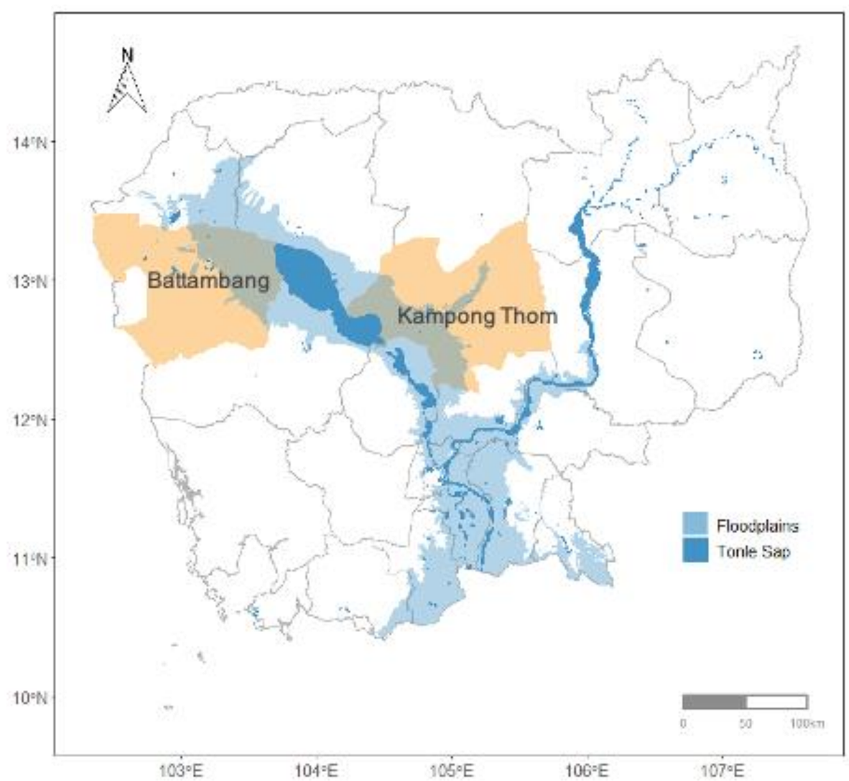

Figure 1. Geographical map of the study sites overlaying the permanent extent of Cambodia's Tonle Sap Lake during the dry season rice production and the extent of floodplains during the monsoon season.

We conducted interviews with local growers and collected field data from 12 farms in Krong Stueng Saen Village in Kampong Thom near the Stung Sen River, a tributary of Tonle Sap Lake. The irrigation is managed by Cambodia Agricultural Value Chain (CAVAC), a local farmers cooperative. Although these farms are located no more than 10 kilometers apart, their crop establishment 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. Sowing times of the farms vary from two weeks to one month. 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 in deciding when to release water to the canals.

Sizes of the farms included in the study ranged from 0.2 to 3.0 ha. Weeds were a common problem in the paddies, occupying almost 20% of the cropping area. Field samplings were done during their DS cropping in 2018 and 2019. We also conducted personal interviews with farmers to survey their planting schedules and crop management practices. Plant and soil samples collected in every farm were used as baseline data for evaluating crop model performance. It was an unusually dry year in Cambodia in 2019. During our data collection, 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 irrigation available. The local government decided to reserve the water supply for the anticipated drought for the rest of the dry season in 2019.

2.1.2 *PhenoRice Method of Detecting Timing and Location of Cropping*

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

Phenological indicators are distinguished by using the Enhanced Vegetation Index (EVI) and Normalized Difference Flood Index (NDFI) spectral indices from the MODIS Terra and Aqua (MOD13Q1 and MYD13) time-series images. 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, followed by EVI profile consistent with the rice's development stages. 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 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 corresponds to crop heading. The MODIS time-series 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 in ENVI®, a software for geographical and remote sensing imagery analysis. In this study, the PhenoRice workflow (see Appendix B) was coded and executed in "R". The required parameters were calibrated and modified by applying the PhenoRice to the geo-coordinates of the rice farms visited during the dry season of 2018 and 2019 (Table 1).

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 DS 2018 and DS 2019.

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
Wet season (WS)	1 March - 30 September	-	Possible planting periods
Dry season (DS)	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}	80 (WS) 90 (DS)	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}	30 (WS) 35 (DS)	days	Maximum difference between identified sowing period and possible anthesis
Δt_{max}	90 (WS) 110 (DS)	days	Maximum difference between identified sowing and possible harvest period

The parameters, especially the minimum and maximum EVI threshold, were calibrated based on the obtained MODIS-processed images of the 17 farms visited in Kampong Thom and Battambang. Adjustment on length of vegetative stage and planting durations were based on the commonly used rice varieties on these sites. Short duration (~90 days) and medium-duration (~100-110 days) varieties were assumed for WS and DS, respectively. Flooded conditions, which suggest land preparation and crop establishment, has a minimum threshold NDVI value of 0.

The 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), Day of Year (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 et al., 2016) in "R". Annual land cover map downloaded from SERVIR-Mekong (https://rlcms-servir.adpc.net/en/landcover/) was used as a supplemental resource to pre-classify rice areas before implementing PhenoRice.

For each year from 2001 to 2019, cropping dates estimated by PhenoRice were compiled with the corresponding pixel count and location, which were later used as input for ORYZA (v3) model simulations to estimate the total production associated with planting date. The annual and total area planted at a given crop establishment date was recorded for each dam-period. The daily mean of planting area for pre- and post-dam was calculated, consequently obtaining the moving time-series average using 8 days 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 *Flooding Estimation*

Time-series NDFI images from 2001 to 2019 were used to verify how flooding influences the timing and area of rice production. A fixed extent was designated to cover Kampong Thom and Battambang province and the percentage of flood pixels, which has a corresponding minimum NDFI value of 0, was obtained for each 8-day temporal image. Percent flooding assigned to a given DOY was compiled for each year and the average for each dam-period was calculated. The moving average of percent flooding for pre-dam and post-dam was calculated with 8-day rolling window based on the temporal resolution of NDFI and DOY images. The relationship between the extent of flooding with the area and timing of cropping at pre-dam and post-dam rice production was evaluated using the Pearson correlation method.

2.2 ORYZA (v3) Model Calibration and Validation

All the production and yield estimations in this study were conducted using the ORYZA (v3) Rice Model (Li et al., 2017), formerly known as ORYZA2000 (Bouman, 2001), developed at the International Rice Research Institute (IRRI). This recently updated version has an expanded ability to model lowland, upland, and aerobic 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, 2009; Yadav et al., 2011; Li et al. 2015; Radanielson et al., 2018).

To test the ability of our crop model to simulate actual farm conditions, we calibrated and validated ORYZA (v3) using field measurements and information gathered from farmer's interviews during DS of 2018 and 2019. Sen Kra Ob and IR 5154 were two commonly planted varieties during our farm visits. Sen Kra Ob is a short-to-medium duration aromatic variety grown for the export market while IR 5154 has a longer growth duration and cultivated in both dry and wet seasons. Prior to our scenario simulations, these two varieties were first calibrated using the measured total dry biomass and phenological information to determine their specific leaf area and partitioning factors (Appendix D). The values were calculated using the auto-calibration tool in the ORYZA (v3) model package. All the other crop parameters were taken from the standard crop values used in ORYZA (v3), which are based on the robustly parameterized IR 72 rice variety. Validation 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 by the model. 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:

$$RMSE = \sqrt{\frac{\sum_1^N (y_i - Y_i)^2}{N}} \qquad (1)$$

$$rRMSE = \frac{RMSE}{\bar{y}} * 100 \qquad (2)$$

$$EF = 1 - \frac{\sum_1^N (y_i - Y_i)^2}{\sum_1^N (y_i - \bar{y})^2} \qquad (2)$$

Observed values are denoted 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.

2.3 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. Specifically for this research, we used the model to estimate the final yield based on the planting date we gathered from PhenoRice, as well as to simulate yield responses due to climate, temperature, N application, and soil nutrient deposits in the form of organic carbon. This recent ORYZA (v3) features two new modules that serve well for our objectives. The soil carbon and nitrogen dynamics module that quantifies the changes in the soil organic carbon and nitrogen content, as well as the soil temperature module that accounts for the daily soil surface temperature to the lower layers by employing Fourier Law. The detailed formulations behind these modules can be referred from Li et al. (2017).

2.3.1 *Farm Data*

We selected 12 rice farms in Kampong Thom and 5 farms in Battambang, making sure that their spread represented the geographic gradient towards the lake. Sowing date, irrigation depth, amount and timing of fertilizer application, and growth stage information of the planted variety were noted in each sample farm. Weight of total biomass and planting density were taken at reproductive stage in DS 2018 (January to February, 2019). During the vegetative stage in DS 2019 (December, 2019), weight of partitioned biomass and planting density were measured. All plant and soil samples were processed at the Soil Science Laboratory of the Royal University of Agriculture in Phnom Penh, Cambodia.

Onsite soil measurements such as soil texture, soil organic matter content, and bulk density, were used as input data for 0 to 15 cm depths. 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 supplement onsite soil information, soil data from 15 to 100 cm depth such as soil texture, soil organic carbon, and bulk density were obtained from SoilGrids[TM] (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 (Saxton and Rawls, 2006) using the downloaded soil texture.

2.3.2 *CLIMATE DATA*

The observed weather data from newly-installed weather stations of Cambodia's Center of Excellence on Sustainable Agricultural Intensification and Nutrition (CESAIN) were used for farm-specific dry season simulations in 2018 and 2019 for ORYZA (v3) model calibration and validation. Because historical weather data were unavailable for Battambang and Kampong Thom from 2001 to 2018, we obtained our temperature, solar radiation, vapor pressure and wind speed data from National Centers for Environmental Prediction Global Forecast System (NCEP GFS) Final, and rainfall from Tropical Rainfall Measuring Mission (TRMM 3B42V7) dataset from 2001 to 2018, 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.

2.3.3 *ESTIMATING PRODUCTION AND YIELD PER ESTABLISHMENT DATE*

We calculated the attainable yield at each sowing date for the dam-periods using ORYZA (v3) to capture the effect of climate conditions from 2001 to 2018 and to estimate the total production associated with a given planting date. In this context, attainable yield is the best possible yield that the model can predict from a given set of inputs (FAO and DWFI, 2015). Same management inputs were used for each yearly simulation, which were based on the farm practices of the farms in Kampong Thom with median harvest yield. Essentially, the only varying factors for these simulations were the daily climate inputs. Employing the total rice area per planting date obtained from PhenoRice, we were able to estimate the total production using the IR 5154 variety. We then compared the harvest yield differences for a given cropping period between pre-dam and post-dam.

2.3.4 *Yield Response Simulations 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 we visited during DS 2019 (Appendix E).

Temperature effects

Among the challenges in Cambodia's rice production is the changing climate. The increasing temperature presents adverse effects on crop growth and development. An increase in temperature between the range of 25 to 35 °C could result in a drastic decline in rice yield (Hussain et al., 2019). It was projected that the mean annual temperature in Cambodia could increase from 1.6 to 2.0 °C by 2100 (WHO, 2016). In 2015, Thoeun (2015) reported that the maximum annual temperature recorded in Cambodia was 38 °C. Using the calibrated IR 5154 variety, 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 to 2018.

Nitrogen application effects

Nutrient management with fluctuating hydrology is challenging for rice cropping (Kato and Katsura, 2014). Wet season rice in Cambodia has always been less productive, with an average of 2.5 t-ha$_{-1}$ during the last 10 years (MAFF, 2018; GAIN, 2019). Farmers face greater risks of crop failure because of unpredictable intensity of flooding and rainfall. The ever fluctuating hydrological conditions give them less incentive to invest on fertilizers and field maintenance. Dry season is more profitable because of better water management control, higher solar radiation, and use of modern rice varieties with better N use efficiency. Moreover, the presence of upstream dams allow irrigation water to be available during the dry season encouraging increased rice cultivation. In this study, we performed ORYZA (v3) simulations with three N application schedules based on our farm interviews (Appendix E) with total N applied ranging from 30 to 200 kg-ha$_{-1}$ per season. The first simulation (S-1) was applying N at two different developmental stages: 1) during early tillering and 2) panicle initiation; the second simulation (S-2) was also twice: 1) during late tillering and 2) booting; and lastly (S-3) was simulating three applications: 1) during early tillering, 2) late tillering, and 3) panicle initiation.

Residual soil organic carbon

The organic matter reserves of the agricultural zone of Tonle Sap's floodplains is replenished as flood pulse from the Mekong River brings a rich mix of sediments during the monsoon season. Dry season rice benefits from this ecosystem services when the water subsides, leaving behind fertile silt deposits. With the dams in place, the water level during the dry season is expected to increase and to stay longer than before. In a comprehensive survey conducted by Arias et al. (2013) on the diverse natural and agricultural vegetation surrounding Tonle Sap floodplains, they determined how different soil properties are influenced by the flood duration. It was evident in their results that there was positive correlation between organic matter content and duration of inundation. However, as the dams control the magnitude of water flow, the nutrient quality of the sediments carried by the flood pulse during the wet season could diminish. This might potentially result to less fertile deposits left in the floodplains come dry season. We then estimated through our model the possible effect of the changing soil organic carbon (SOC) content of the soil to the harvest yield. With the onsite SOC measured during the start of dry season in 2018 as reference, we estimated the final yield if SOC is decreased by to 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 and pre-processed in "R" through 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., 2016), 'raster' (Hijmans and van Etten, 2012), 'rgeos' (Bivand and Rundel, 2017), 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 et al., 2020), and ‘base’ (R Core Team, 2019) packages in “R”.

3 RESULTS

3.1 LOCATION AND TIMING OF RICE PRODUCTION

The effect of the increasing presence of hydropower dams in the Mekong River to the timing and location of rice cultivation in the Tonle Sap floodplains was detected using PhenoRice. To graphically illustrate the influence of the flood inundation extent to the temporal cropping distribution, we overlaid the rolling average of the flooded area for the entire cropping season with the percent of area planted at a given crop establishment period (Fig. 2). Take note that depth was not accounted for in this comparison. Extent of flooding is indicated by the shaded blue area while the normalized total area of cropping seasons is on the foreground. Before analyzing this relationship, it is worthwhile to first evaluate the difference between the magnitude of flooding between the two dam-periods by looking at the result of the student *t-test* in Table 2. There was no significant difference between the overall magnitude of flooding between the dam periods in the two sites. However, monthly variability showed the significant change in hydrology, especially during dry season. Inundation was observed to be higher at post-dam specifically in the months of November and January for both in Kampong Thom and Battambang floodplains. Significant decrease in overall percent flooding during the monsoon season was observed in Battambang at post-dam.

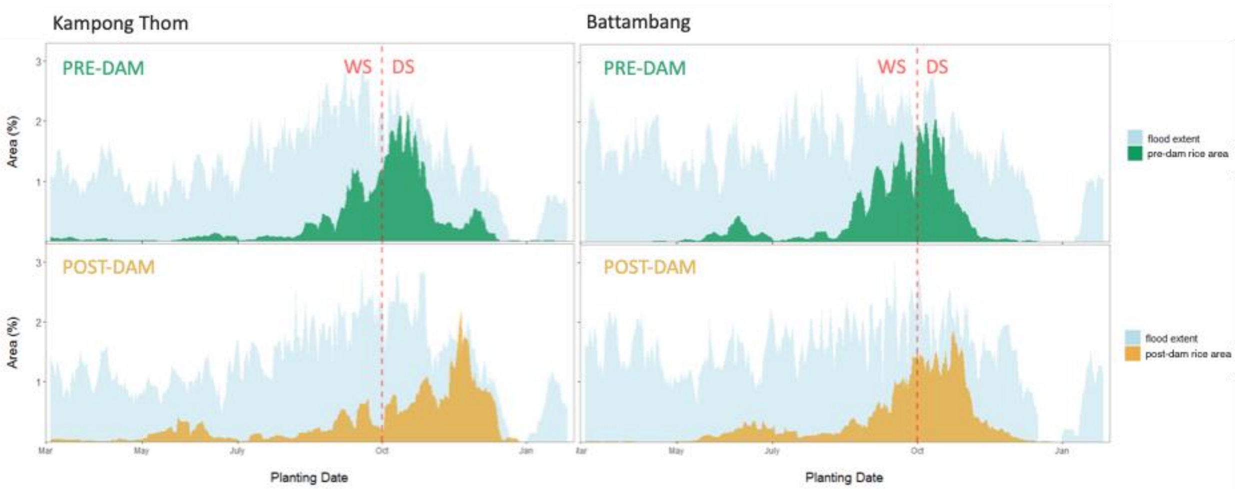

Figure 2. Relationship between flooding extent and timing of crop establishment in Kampong Thom and Battambang provinces at pre-dam and post-dam. Flooding extent was estimated using the MODIS NDFI time series products. Estimated rice areas by PhenoRice is presented in 8-day rolling average percentage. Dotted red line delineates wet season (WS) and dry season (DS).

Table 2. Mean comparison of percent flooded area during rice production at pre-dam and post dam.

Month/Season	Kampong Thom (% flooded area)			Battambang (% flooded area)		
	Pre-dam	Post-dam	*p-values*	Pre-Dam	Post-Dam	*p-values*
Average flooding	1.30	1.33		1.51	1.48	
Wet season	1.43	1.37		1.72	1.61	**
March	1.08	1.12		1.67	1.64	
April	1.08	1.04		1.57	1.44	
May	0.86	0.95	*	1.25	1.20	
June	1.15	1.08		1.52	1.47	
July	1.54	1.40		1.84	1.64	*
August	1.97	1.80	*	2.01	1.81	
September	2.30	2.16		2.18	2.08	
Dry season	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	***

*$p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$*

Table 3. Mean comparison of total rice areas detected by PhenoRice during pre-dam and post dam.

Month/Season	Kampong Thom (x100 ha)			Battambang (x100 ha)		
	Pre-dam	Post-dam	*p-values*	Pre-Dam	Post-Dam	*p-values*
Total area	42.59	109.99	***	233.82	219.81	
Wet season	15.59	27.53	**	124.06	102.73	
March	0.41	1.00	**	0.05	0.72	**
April	0.10	0.43	*	0.32	0.17	
May	0.13	4.63	***	4.19	3.44	
June	1.25	3.28	**	13.63	20.47	
July	0.68	1.60	**	3.89	8.65	
August	2.55	4.25		18.55	15.20	
September	10.48	12.35		83.43	54.08	
Dry season	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	***	-	-	

*$p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

As for the cultivated rice areas, there was a significant shift in crop establishment schedule (Fig. 2 and Table 3) and increase in rice cultivation areas during the dry season at post-dam, which was more evident in Kampong Thom. Crop establishment increased significantly from November to December. During pre-dam, sowing was commonly done in October, the onset of DS. In the case of Battambang province, the results of the two-tailed student *t-test* in Table 3 did not show significant difference in the total rice areas between pre-dam and post-dam. In addition, there was no significant difference in the detected total rice areas per season between the dam-periods. Extended crop establishment was observed in November to December. According to published data (MAFF, 2017; MAFF 2018), Battambang province has higher production during WS than DS, however PhenoRice failed to capture this trend.

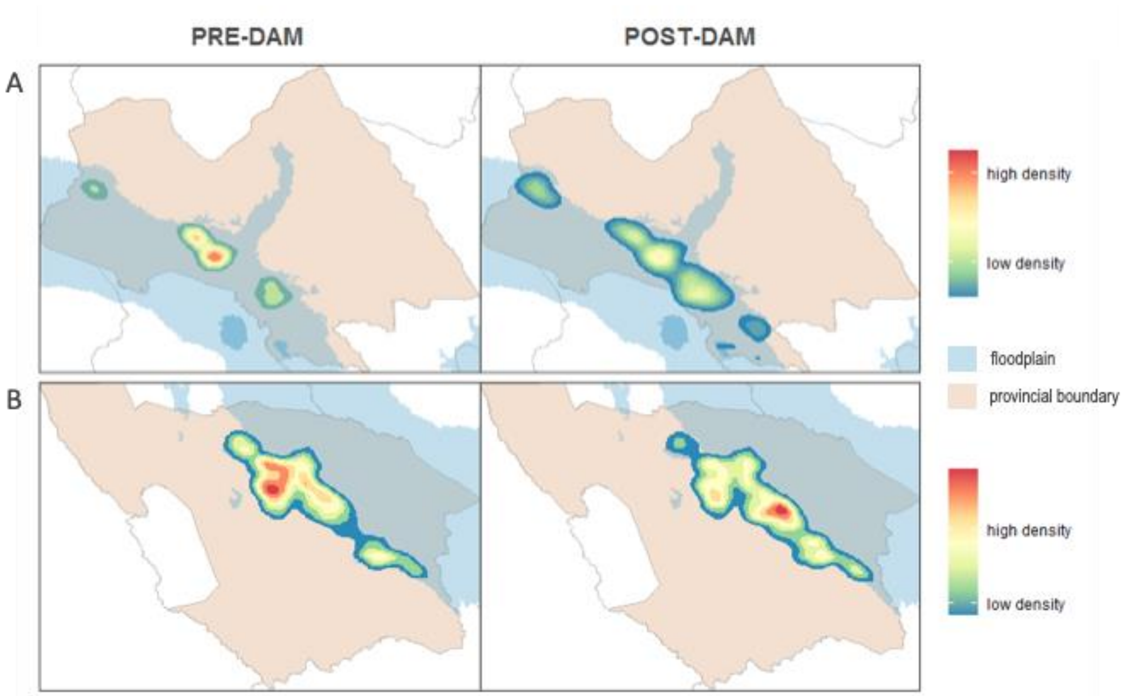

Figure 3. Heat maps of cultivated rice areas showing the locations and clustering of farms in Kampong Thom during the dry season (A) and Battambang during the wet season (B) at pre-dam and post-dam as estimated by PhenoRice. Due to their location in the Tonle Sap Lake, Kampong Thom experiences early and longer flooding while Battambang experiences late inundation and early flood recession.

PhenoRice also allowed us to examine the spatial distribution of rice farms in the Tonle Sap floodplains, which were illustrated by the density maps of the different planting seasons in Fig. 3. The heat map of Kampong Thom showed that farms were more sparsely distributed during post-dam while farms were more clustered during pre-dam (Fig. 3A). The expansion of rice cultivation at post-dam occupies the same areas that were only identified for WS production (Appendix C). The locations and area distribution detected were generally similar for both pre- and post-dam periods in Battambang during WS (Fig. 3B). Cropping was denser on the northwest side where Kamping Pouy reservoir is situated during pre-dam, however, an apparent change in hotspots can be observed at post-dam. Concentration near the reservoir declined while most cultivations shifted towards the direction of the lake.

We further determined the correlation between timing of inundation and cropping time and comparing the planting periods during pre-dam and post-dam (Table 4). Pearson correlation results confirmed that flooding has a direct influence on the overall crop establishment schedule at pre-dam given by the coefficient values of 0.51 and 0.58 for Battambang and Kampong Thom provinces, respectively. Breaking down into cropping seasons, there was even higher positive correlation during DS in both sites (Table 4).

Table 4. Pearson correlation between flooding extent and detected rice-cultivated areas to verify the influence of flooding to the timing of cropping.

Farm/Season	Pre-Dam	Post-Dam
Kampong Thom	0.58	0.36
Wet Season	0.67	0.63
Dry Season	0.81	0.49
Battambang	0.51	0.53
Wet Season	0.51	0.48
Dry Season	0.71	0.74

Correlation decreased more evidently in Kampong Thom at post-dam. Note that earlier findings showed significant increase in rice cultivation at post-dam (Fig. 2), a fairly spread-out distribution of planting locations along the floodplains (Fig. 3A), and an increase of DS water extent in the province (Table 2). At post-dam, correlation between flooding and timing of sowing decreased dramatically from 0.81 to 0.49 during the dry season in Kampong Thom and more areas shifted their planting to the latter part of the season (Fig. 2). Opposite was observed in the correlation values in Battambang (Table 4). Positive correalation between planting time and flooding increased in the dry season from 0.71 to 0.74 as the extent of the lake increased in November and December (Table 3). Correlation between flooding and cropping schedule decreased during the wet season at post-dam for both provinces.

3.2 Crop Model Calibration and Validation Results

Utilizing the biomass measurements we gathered from Kampong Thom and Battambang, we first calibrated our two sample crop varieties to establish the reliability of succeeding yield response scenario analyses. Weight of total dry biomass measured from eight farms in Kampong Thom in DS 2018 were used to calibrate IR 5154 variety, while measurements from four farms in Battambang in DS 2018 and four farms in Kampong Thom in DS 2019 were used for Sen Kra Ob. Plant samples were taken mostly around the reproductive stage in DS 2018 and vegetative stage in DS 2019. For the validation, total dry and partitioned biomass were used, all sampled from Kampong Thom farms. Validation was only employed for IR 5154 because of insufficient data points available for Sen Kra Ob. Plotted results of calibration and validation were shown in Fig. 4 with the 1:1 line to visually compare the differences between the model estimates and actual measurements. The corresponding values of the goodness-of-fit parameters were listed in Table 5. The calculated EF for the calibration was 0.49 and 0.64 for IR 5154 and Sen Kra Ob, respectively. Model is considered acceptable if threshold values are $0.5 < EF$ (Moriasi et al., 2007). Other parameters used, such as RMSE, rRMSE, and R_2 to verify the ability of the model to estimate actual farm conditions are listed in Table 5. Validation results showed improvement in EF and R_2, particularly for total biomass. Comparing the measured and modeled dry weight of partitioned stem and green leaves gave EF values of 0.56 and 0.35 for green leaves and stem, respectively. Total biomass and stem were underestimated as indicated by the 1:1 line.

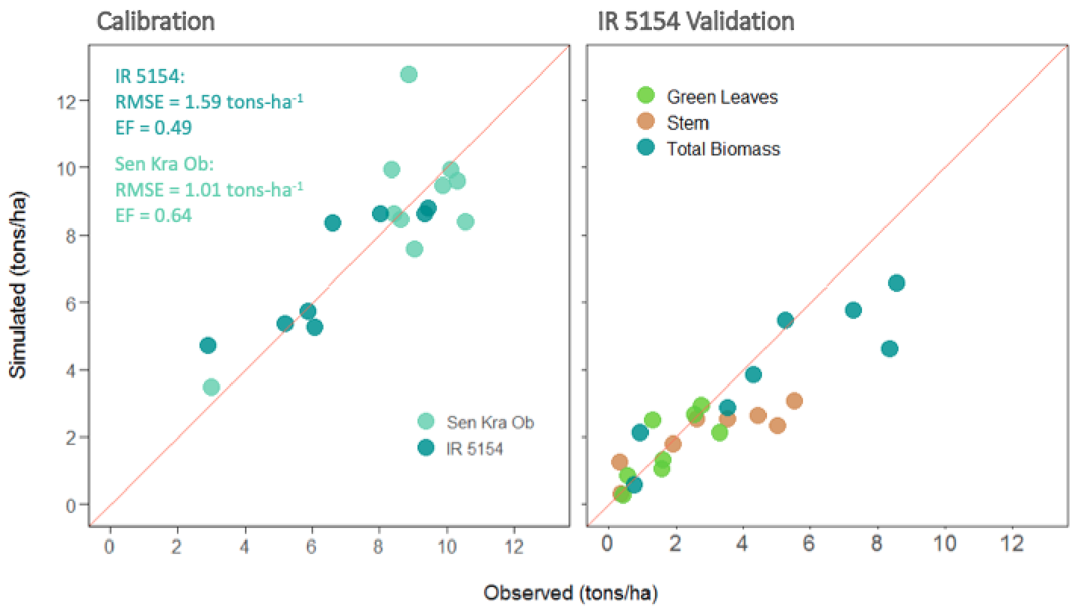

Figure 4. Calibration and validation of IR 5154 and Sen Kra Ob varieties for ORYZA (v3) simulations. Calibration was based on the total biomass measured in the sample farms. Validation was performed only for IR 5154. Partitioned and total biomass gathered during DS 2019 were used for validation with corresponding values of the goodness-of-fit parameters listed on Table 5.

Table 5. Calculated RMSE, rRMSE, EF, and R_2 during calibration and validation. Observed data used for calibration were taken at late vegetative to reproductive stage of 2018 dry season, while validation data were measured at vegetative stage of 2019 dry season.

	Parameterization				Validation			
	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

3.3 Production and Yield Simulation Results

The estimated yield by the crop model was multiplied with the identified rice areas by PhenoRice to calculate the total production for a given crop establishment date. Effects of climate, the amount and timing of N applications, variations in SOC concentrations, and changes in daily average temperature on the harvest yield were also simulated using the ORYZA (v3) model.

3.3.1 *Effect of Climate to the Total Production and Yield Per Planting Time*

Using our crop model, we simulated the effect of daily weather conditions on the final yield. The attainable yield for a given planting date was calculated (Fig. 5). Subsequently, we estimated the total harvest per planting time using the total area derived from PhenoRice. For this simulation, we used IR 5154 and focused only in Kampong Thom province. The daily weather data was derived from GFS and TRMM from 2001 to 2018.

By estimating the attainable yield for a given planting time, we were able to illustrate the effect of climate to the harvest yield (Fig. 5). Cropping dates that resulted to higher yields were mostly observed during the dry season in both dam periods. Calculated yields for both pre- and post-dam range from 6 to 7 t-ha$_2$. Post-dam yield curve followed almost the same pattern as pre-dam, except during the months of January and February. By visual inspection, the increasing area of total production coincided on the dates that gave higher paddy yields, which was from September to December.

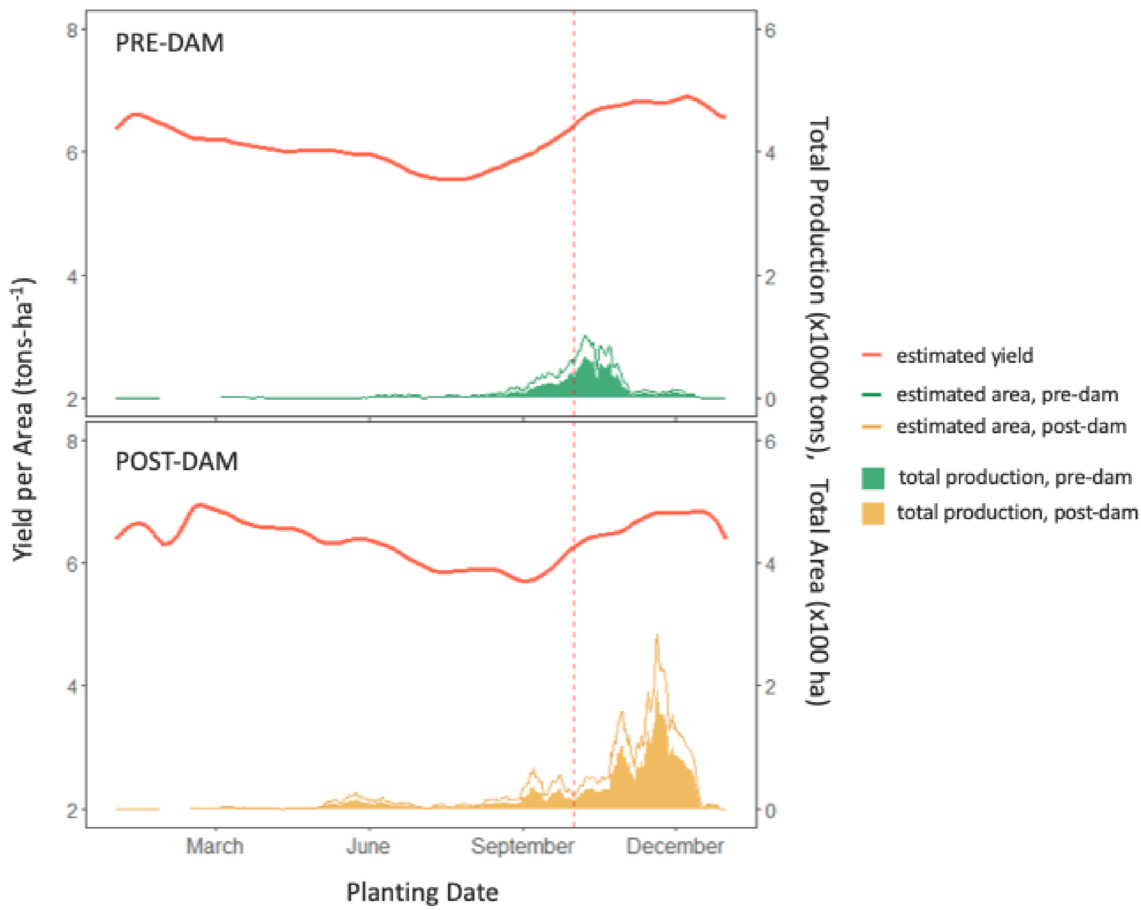

Figure 5. Estimating the total production per day in Kampong Thom province by multiplying the attainable yield estimated by ORYZA (v3) and the area detected by PhenoRice at pre-dam and post-dam. IR 5154 variety was used for the simulations and agronomic inputs were based on the farm practices that produced the median yield during the site visit.

The annual total production for the sample provinces was estimated and presented in the bar graph in Fig. 6. The only available official production data gathered from MAFF for the two sample provinces was for 2016 and 2017, represented by the points in the graph. Thus, validation of the estimated productions to the actual provincial data was inadequate. From the limited data points, there was noticeable underestimation in total production by the combined PhenoRice and ORYZA (v3), which could also be likely true in the previous years where official data were not available.

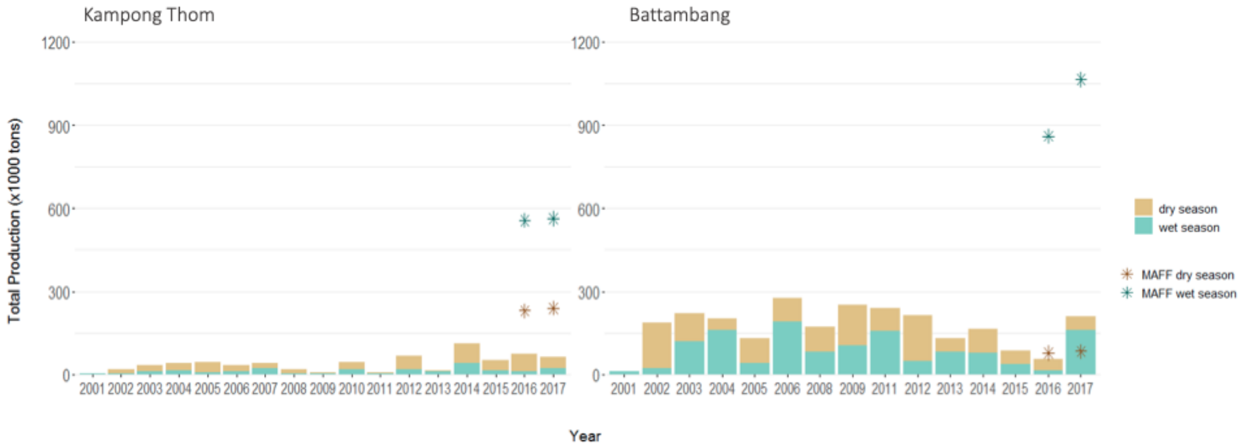

Figure 6. Estimating annual seasonal total production based on the attainable yield by ORYZA (v3) and detected rice area by PhenoRice in Kampong Thom and Battambang. Official data from MAFF in 2016 and 2017 are overlaid as individual data points to compare with estimated results.

3.3.2 *Amount and Timing of N Application*

Three scenarios were considered for N levels applied at different growth stages of rice, namely, S-1 where N is applied at tillering and panicle initiation (PI); S-2 at late tillering and booting; and S-3 at early tillering, late tillering, and PI. All treatments were simulated with 30 to 200 kg-ha$_{-1}$ total N applied per cropping season. Yield responses show that optimum N required for IR 5154 is around 100 kg-ha$_{-1}$ with attainable yield of about 6.2 t-ha$_{-1}$ (Fig. 7A). These values were achieved by treatments S-1 and S-2 faster than treatment S-3. Applying N twice during the season, one at vegetative and one at reproductive stage, obtained higher yield if the total N application was less than 100 kg-ha$_{-1}$. There was no apparent yield advantage for any N applied greater than 100 kg- ha$_{-1}$ across all treatments.

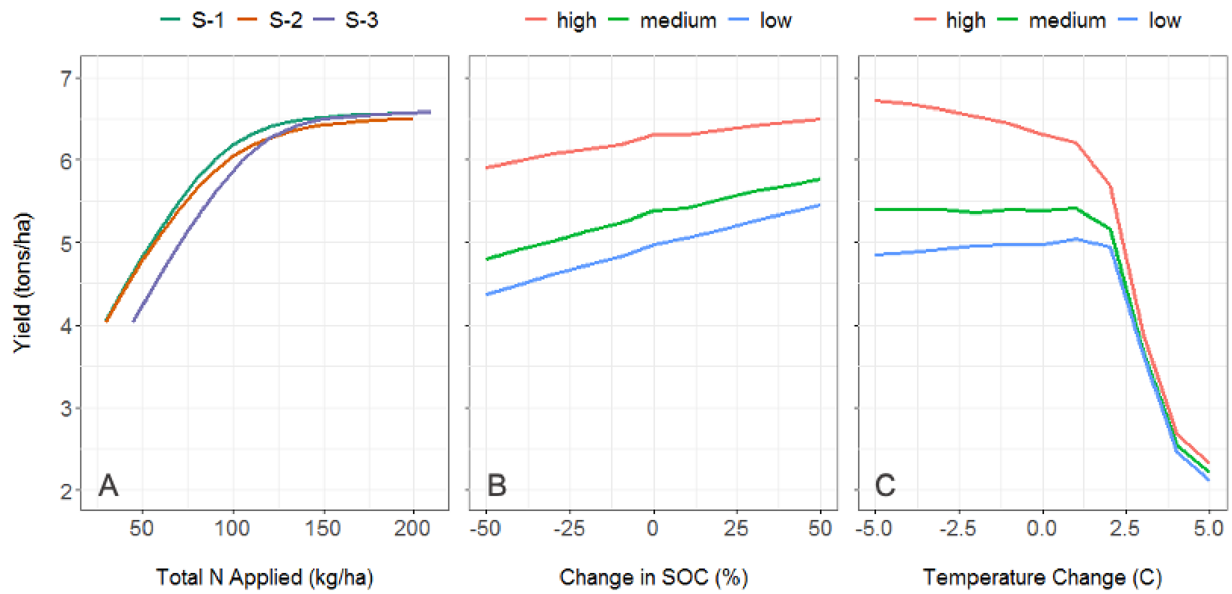

Figure 7. Simulating yield response to A) N amount and timing of application, B) reduction and increase of soil organic carbon, and C) change in temperature. For N simulations (A), S-1 is applied at early tillering and panicle initiation (PI); S-2 at late tillering and booting; and S-3 at early tillering, late tillering, and PI. For soil organic carbon (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.

3.3.3 *Soil Organic Carbon*

Soil in floodplains tend to be more fertile after monsoon flood recedes and nutrient-rich sediments are brought ashore from the upstream. Knowing that soil fertility affects yield, we also conducted ORYZA (v3) simulations at varying soil organic carbons (SOC). We used the baseline SOC collected in December 2018 in the 12 farm sites in Kampong Thom to verify the yield response if SOC is reduced from less than 50% and increased to more than 50%, as an attempt to capture the natural cyclic change in soil fertility in the Tonle Sap floodplains. 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 productivity of farm management practices gathered from the site were tested. The treatments were identified as follows: low, refers to the practices that produced the lowest actual yield; medium for the median yield; and high for the management that obtained the highest yield during the 2019 DS.

Simulation results (Fig. 7B) showed that regardless of the management practice, IR 5154 tends to increase yield at the same rate with increasing SOC. All three management practices improved their yield by no more than 0.5 t-ha^{-1} if the current SOC is increased to 50%. Low management could increase their current yield by 0.47 t-ha^{-1} if SOC increases by 50%. Medium and high farm management treatments could increase by 0.38 t-ha^{-1} and 0.2 t-ha^{-1}, respectively. The relatively flatter slope shown by the best farm practice indicated that there was not much value added to their yield with increased SOC.

Decreasing the amount of SOC by 50% caused greater impact on yield, especially for medium- (0.50 to 0.58 t-ha^{-1}) and low-managed farms (0.46 to 0.50 t-ha^{-1}). The yield penalty for decreased SOC was greater than the gain from increased SOC. With IR 5154, 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.

3.3.4 *Temperature Increase*

We also simulated how change in temperature could affect the harvest yield with varying management practices in Kampong Thom, employing the same scenarios used in SOC sensitivity analysis. The average minimum and maximum daily temperature for this simulation were 23 and 35 °C, respectively. Results in Fig. 7C showed that temperature effects were more evident between 2 to 2.5 °C increase in temperature, given by the abrupt decline in harvest yield. Medium- and low-managed farms have less sensitivity to up to 5 °C decrease in the daily average temperature. Yield penalty with increasing temperature is more observable in farms under high agronomic management. Any temperature increase of at least 2 °C caused abrupt yield loss regardless of the farm management treatment.

We then verified the possible effect to the harvest yield if the temperature during pre-dam and post-dam cropping was increased by 3 °C in Kampong Thom and Battambang. It is aparent in Fig. 8 how the yield decreased by up to 4 t-ha-1, especially in the early part of the year at post-dam in both provinces. The dates that were consistently predicted to give higher yields were no longer considered favorable for rice production, particularly in late December to the first quarter of the year. Same management conditions were applied for the total production simulations conducted in Fig. 5.

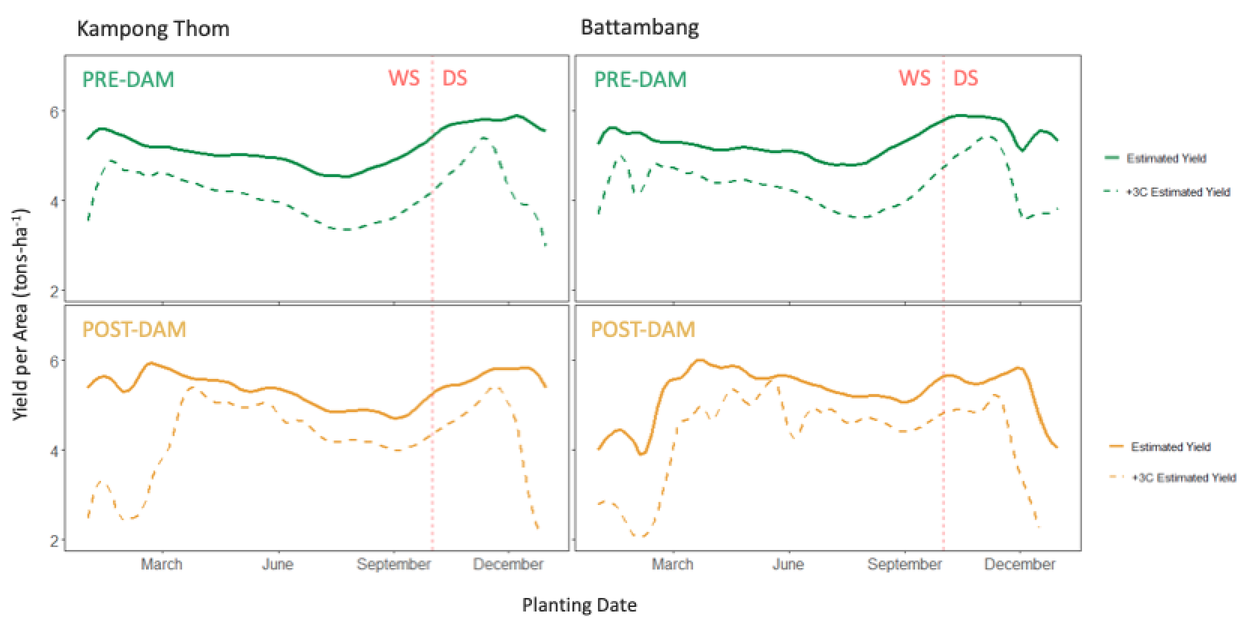

Figure 8. ORYZA (v3) estimation of the attainable yield in Kampong Thom and Battambang at pre-dam and post-dam when temperature was increased by 3 °C from the average temperature. Simulations were conducted using IR 5154 and based from the farm practices that produced the median yield during the site visit.

4 DISCUSSION

4.1 ANALYSIS ON THE CHANGES IN CROPPING PATTERNS

We recognize that PhenoRice needs thorough validation especially on the WS results. Persistent cloud cover and precipitation were common sources of noise during this cropping period and Pixel Reliability indices were not sufficient to correct for this error. Moreover, the main focus of PhenoRice is to estimate crop establishment based on phenological signals, and has a known issue of underestimating rice areas (Busetto et al., 2019). Ground truthing is also necessary to validate results. 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 to be considered as validation data points. The official MAFF reports showed that PhenoRice consistently underestimated the total production in Kampong Thom and Battambang, especially for WS. Working around the limitations and the low level of accuracy of PhenoRice results, there were important observations on how hydrology is influencing the planting time, area, and location, especially during in DS , that can be verified and studied further.

The location of Battambang and Kampong Thom relative to the Tonle Sap Lake illustrates how rice production is dependent on accessibility to floodwater. Kampong Thom gets flooded ahead of Battambang. The latter drains the water first and the former experiences longer inundation. One important pattern that we detected was the shift in the density of cropping in Battambang to locations closer to the lake during the WS (Fig. 3), which was possibly due to early flood recession. The spatio-temporal changes that we observed through PhenoRice during DS can be considered more reliable to describe the rice cropping patterns because of less persistent cloud compared to WS.

Expansion of Tonle Sap's permanent lake extent makes irrigation more available during DS. In Kampong Thom province, there was an increase in cropping areas during DS. The farms appeared to have spread out to locations that were identified only for wet season rice at pre-dam (Fig. 4A and Appendix D). This implies that inundation might have been extended in those areas making them suitable for irrigated rice. It then provides rice farmers more flexibility in deciding when to start their cropping, which was observed in the changes in planting dates that PhenoRice detected where planting dates shifted from early to mid-part of DS (Fig. 2 and Appendix C). It also explains the decreased correlation between the timing of planting and flooding at post-dam in Kampong Thom (Table 4). There is less pressure in maximizing the use of the available floodwater before it drains for the rest of DS. On the other hand, if indeed the floodwater subsides sooner at the onset of DS and the extent of the remaining water during the dry season increases, the changes in planting distribution observed in Battambang illustrates how areas in the northern part of the lake experience early flood recession (Fig. 3B), thereby taking advantage of the available irrigation before it subsides.

To increase the certainty of the changes in the temporal and spatial cropping patterns that we detected through PhenoRice, further studies using high resolution satellite images and more *in situ* validation is recommended. It is also important to recognize that other possible factors could contribute to the changing Tonle Sap hydrology, such as the frequency of drought occurrence that could cause less flooding during WS.

4.2 Analysis on Yield and Production Simulation Scenarios

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 taken during DS of 2018 and 2019. Despite the limited sample points, acceptable goodness-of-fit was achieved during the calibration. We decided that the R_2 values (0.48 for IR 5154 and 0.74 for Sen Kra Ob), rRMSE (18.0% for IR 5154 and 14.6% for Sen Kra Ob), and EF (0.49 for IR 5154 and 0.64 for Sen Kra Ob) for the calibration were reliable enough to perform our simulation objectives. Plotting them in 1:1 line in Fig. 4 showed that the variability between the observed and simulated values were within acceptable limits. Validation results for IR 5154 were generally satisfactory, with improved goodness-of-fit for EF and R_2 especially for total biomass (Fig. 4 and Table 5). We put less priority in obtaining high model accuracy, rather, we aim to adequately provide yield trends through the ORYZA (v3) model's ability to show responses from our variables of interest.

Total production estimated from combined PhenoRice and ORYZA (v3) results was underestimated (Fig. 6). This discrepancy could be attributed mainly to the underestimated areas detected by PhenoRice, especially during WS where cloud cover is a common source of error. In most cases, the estimated annual production was able to show that production in Kampong Thom tends to be higher during DS and the higher production in Battambang during WS.

We focused our yield simulations on DS as dam constructions upstream are predicted to open up more farmlands for crop productions. All yield response experiments were carried out using the validated IR 5154 variety. Manipulating farm management parameters was also more meaningful because the farmers tend to invest more time and inputs during DS. There are more variables that the farmers can control, such as the delivery of water and fertilizer application that could result in better yield returns. Although DS yield is at least 50% higher than wet season, the former only contributes to 20% of total annual rice production (Smith and Hornbuckle, 2013).

Limited nutrient availability is one of the major reasons for low productivity of rice in Cambodia (Kong et al, 2020). As reliable irrigation becomes more accessible for DS cropping, farmers have better opportunity to maximize productivity and profitability from investing on chemical fertilizers. Our N sensitivity simulations provide information on the efficient timing of application of N fertilizer during the planting season. ORYZA (v3) results illustrated that once the maximum N threshold was reached (around 100 kg-ha^{-1}), any additional N amount no longer contributed any considerable increase in yield. 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 100 kg-ha^{-1}. During our site visits, majority of farmers in Kampong Thom apply less than 100 kg-ha^{-1} of N fertilizer (Appendix E).

When SOC was reduced by 50%, the simulated rate of yield lost was greater than the yield gained if SOC was increased by 50% (Fig. 7B). This result asserts that natural enhancement of soil fertility be maintained in the Tonle Sap floodplains. Not only is it sustainable for the environment but 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. This puts the farmers in 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.

Droughts are occurring more frequently in Cambodia and the country's mean temperature is increasing by 0.02 °C annually since 1950 (Thoeun, 2015). There are instances when cropping is halted because there is no reliable irrigation caused by low water reserves from drier rainy season. By 2060, the mean annual temperature in Cambodia is predicted to increase by 0.7 to 2.7 °C from the present conditions (World Bank, 2018). Results of ORYZA (v3) simulations predicted that an increase of at least 2 °C in the current temperature was critical and could cause significant yield decline. The window of planting where farmers can obtain the highest attainable yield was also projected to be shortened (Fig. 8). Sowing in late December to the first quarter of the year was predicted to suffer higher loss because of temperature increase.

Yield simulations from ORYZA (v3) generated essential information about the effects of various farm management practices, soil fertility, and increasing temperature to the productivity of rice production and yield.

5 CONCLUSION

The annual flow of monsoon flood from the Mekong River that fills the Tonle Sap Lake with water, fish, and nutrients sustained Cambodia's rice cultivation for hundreds of years. This unique hydrology provides irrigation support in the form of flood water and natural fertilizer support in the form of nutrient-rich sediments delivered to the floodplains. However, this natural cycle is slowly altered by the increasing hydropower dam developments in the Mekong River in recent decades. Examining the rice cultivation in Battambang and Kampong Thom using PhenoRice gave a brief view of the changes in cropping patterns in two different locations of Tonle Sap floodplains. Although the ability of the model to detect rice areas needs further validation, the results of this study provided important observations to streamline the focus for future research. Being situated in the southern part of the lake, Kampong Thom is subjected to earlier and more prolonged inundation than Battambang, which is located at the farther northwest. We observed that with increased floodwater during the dry season in Kampong Thom, rice cultivation has intensified and became more spatially distributed. As the dams control the discharge of water downstream, irrigation becomes more available allowing farmers more flexibility on the timing of crop establishment and opening up more areas for rice cultivation. On the other hand, the decreased flooding extent during the wet season necessitates the efficient utilization of irrigation resources. This entailed taking advantage of the available flood water until it subsides and eventually tapping on the established irrigation system, which was exemplified in Battambang where cropping time and location were adjusted without changes in total area of production.

As rice production adapts to these hydrological changes, we also verified the contributions of farm management practices, soil fertility, and increasing temperature to improve the paddy yield in Cambodia. Soil fertility in Cambodia is low and the commercial fertilizers are either expensive or substandard. Investing on chemical fertilizer inputs would mean applying the recommended amount at the appropriate timing to be cost-effective. ORYZA (v3) crop simulations show that 100 kg-ha^{-1} was the optimum N required to get the attainable yield. Applying N once during vegetative and another one during the reproductive stage was the efficient schedule, especially for farms that apply less than 100 kg-ha^{-1} of total N. Farmers can also take advantage of the nutrient-rich silt deposits left in the Tonle Sap floodplains when the monsoon floods recede. Modeling the decrease and enhancement of residual soil organic carbon showed that about 0.2 to not more than 0.5 t-ha^{-1} can be added to the yield if SOC is increased by 50%. However, these benefits may not be attained if the quality of sediments from upstream declines as the nature-driven flow is controlled by the dams. Our simulations even show greater yield loss from reduced SOC than the potential gain if SOC is increased. We also identified that increasing the current average temperature by 2 °C is critical for crop production. Any increase could lead to drastic yield loss and could shorten the ideal planting window for sowing, especially during the dry season.

Determining these changes in rice production and yield is critical in decision-making and forecasting related to food security and water resource management in the Lower Mekong Region. Although the future of Cambodia's rice production looks promising, there is also a need to examine its impact on the Tonle Sap ecosystem as a whole. Water resource management is essential in ensuring equitable and sustainable distribution of water for humans and natural ecosystems. Grasslands and flooded forests, which serve as spawning grounds for fishes and act as buffers from extreme typhoons, are converted to croplands during the dry season. Removing forest covers also threatens the habitats of bird species living and migrating in the lake. Application of chemical fertilizers could introduce toxic substances that could harm the thriving rich fisheries. A holistic approach with different stakeholders working together is imperative to mitigate the harmful effects of dams to the Tonle Sap ecosystem. The important decision of when and where to cultivate rice would provide insight to policymakers to set guidelines and boundaries that will be equitable to local communities -- the farmers, forest people, and fishermen.

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Appendix A. Official Rice Production Data from Cambodia's Ministry of Agriculture and Forestry and Fisheries

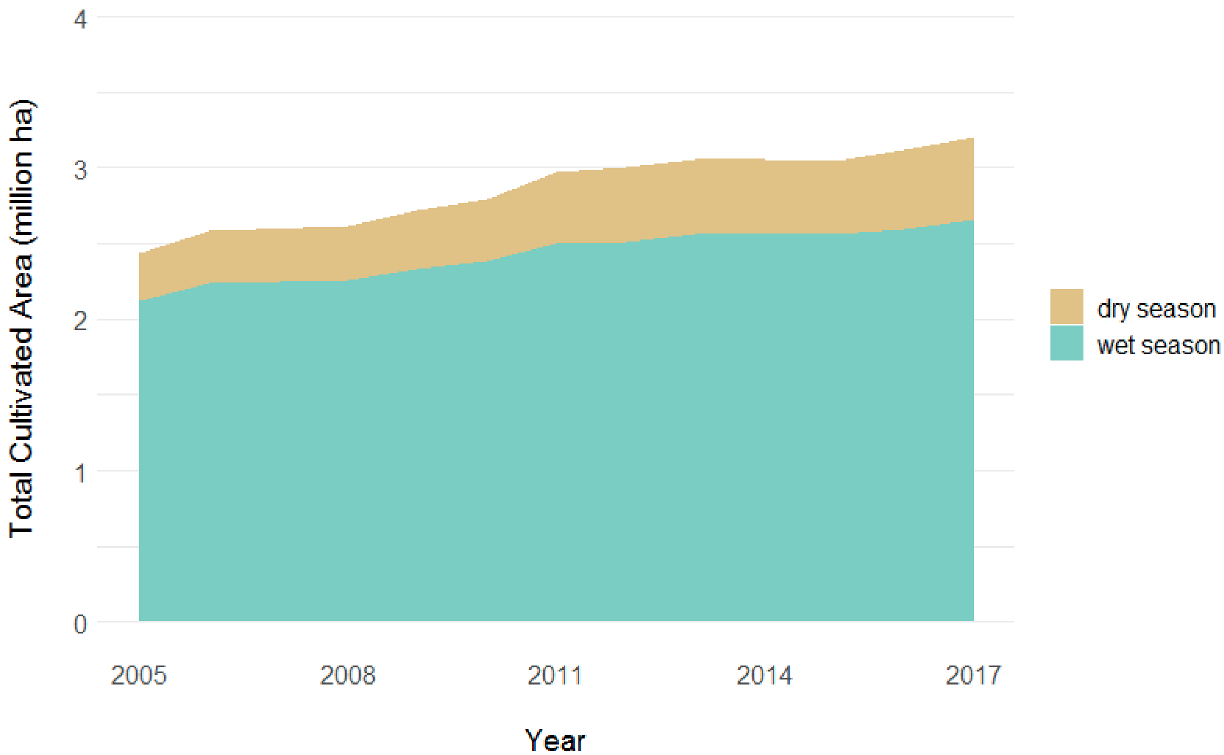

Figure A.1. Annual total rice cultivation in Cambodia from MAFF Annual Report (2018).

Appendix B. Phenorice Algorithm Workflow

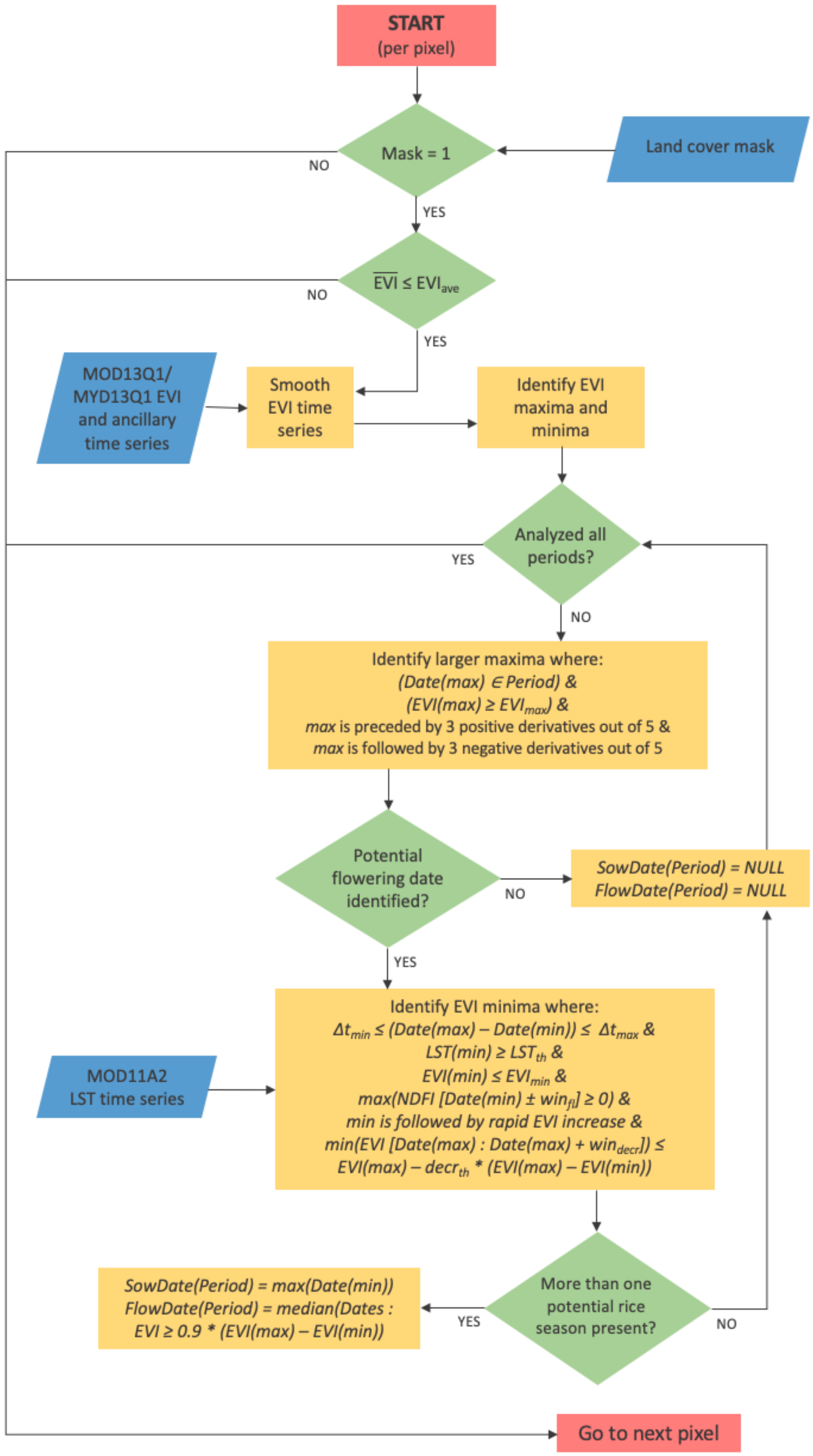

Figure B.1. The PhenoRice algorithm formulated by Boschetti et al. (2017) to extract pixel-based spatio-temporal information of rice production.

Appendix C. Cultivated Rice Areas Estimated by PhenoRice

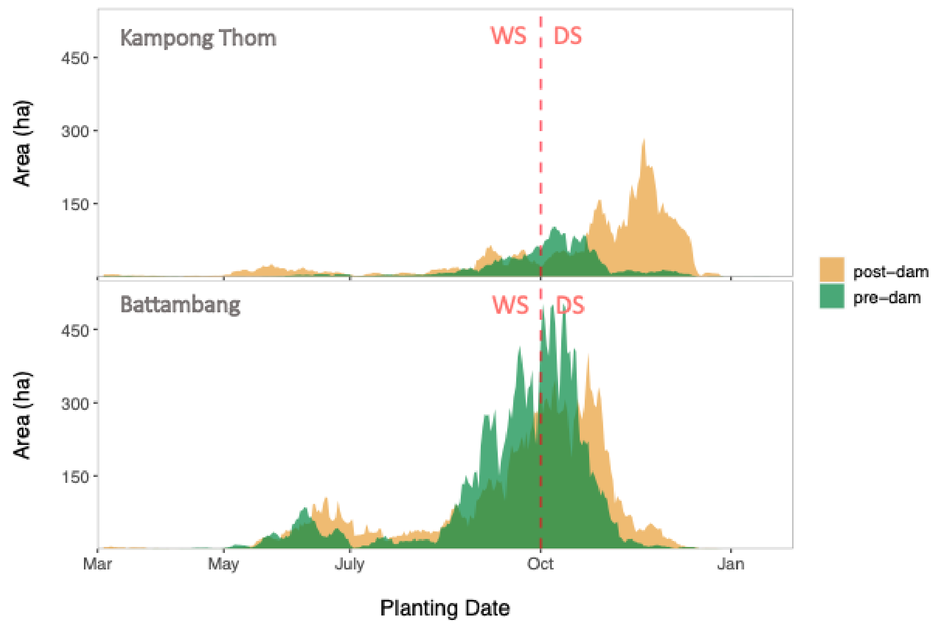

Figure C.1. PhenoRice results showing the 8-day rolling mean of the total rice cultivated area at a given planting time in Kampong Thom and Battambang province. Red line delineates wet season (March to September) and dry season (October to January).

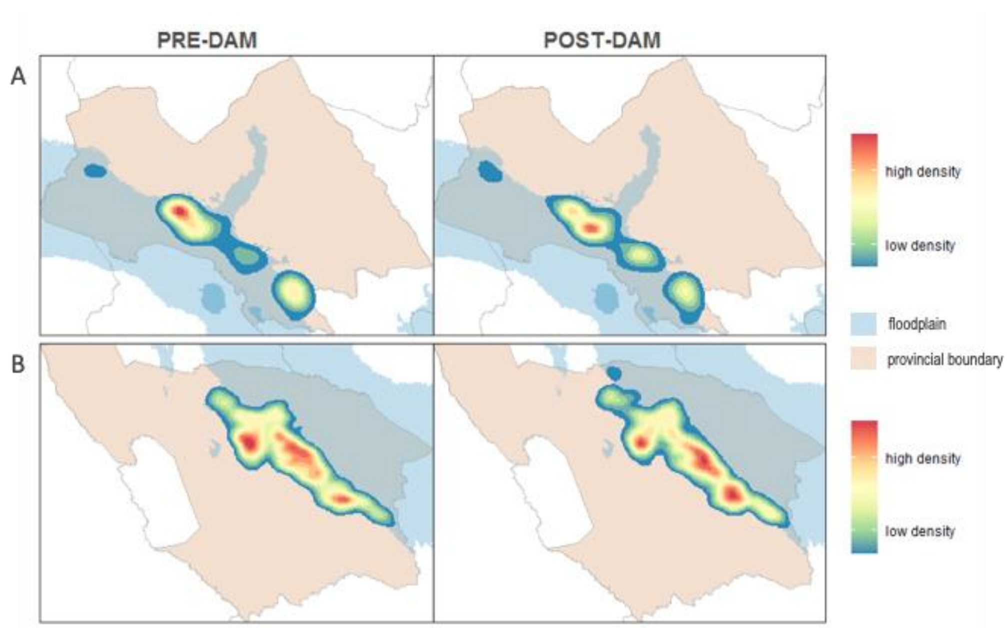

Figure C.2. Heat maps of cultivated rice areas showing the locations and clustering of farms in Kampong Thom during the wet season (A) and Battambang during the dry season (B) at pre-dam and post-dam as estimated by PhenoRice. The floodplain area shown is the officially recognized floodplain map of Tonle Sap.

Appendix D. Calibrated Crop Parameter Values

Table D.1. List of crop parameters calibrated for IR 5414 and Sen Kra Ob varieties. Other model parameter values were based on IR 72, the standard crop variety used in ORYZA (v3).

ORYZA Crop Parameter	Parameterized Values			Units	Description
	IR 72[z]	IR 5154	Sen Kra Ob		
SLA = a + b * exp(c * DVS - d)				ha leaf * kg^{-1} leaf	Smooth function between specific leaf area (SLA) and development stage (DVS[Y]) by supplied function parameters a, b, c, and d
where: a	0.0017489	0.0016051	0.0015709		
b	0.0025700	0.0032596	0.0030549		
c	-4.5	-4.5	-4.5		
d	0.06907701	0.0668492	0.0687282		
SLAMAX	0.0032229	0.0031060	0.0027724	ha leaf * kg^{-1} leaf	Maximum value of SLA
FSHTB	0.00, 0.8438, 0.43, 0.9946, 1.00, 1.0000, 2.50, 1.0000	0.00, 0.7131, 0.43, 0.9012, 1.00, 1.0000, 2.50, 1.0000	0.00, 0.8819, 0.43, 0.7598, 1.00, 1.0000, 2.50, 1.0000	-	Table of fraction total dry matter partitioned to the shoot (2nd column) as a function of development stage (1st column)
FLVTB	0.00, 0.8569, 0.50, 0.3982, 0.75, 0.4837, 1.00, 0.0000, 1.20, 0.0000, 2.50, 0.0000	0.00, 0.8203, 0.50, 0.2165, 0.75, 0.6858, 1.00, 0.0000, 1.20, 0.0000, 2.50, 0.0000	0.00, 0.8413, 0.50, 0.3332, 0.75, 0.3995, 1.00, 0.0000, 1.20, 0.0000, 2.50, 0.0000	-	Table of fraction dry matter partitioned to the leaves (2nd column) as a function of development stage (1st column)
FSTTB	0.00, 0.1431, 0.50, 0.6018, 0.75, 0.4648, 1.00, 0.3253, 1.20, 0.0121, 2.50, 0.6578	0.00, 0.1797, 0.50, 0.7835, 0.75, 0.2810, 1.00, 0.4801, 1.20, 0.0160, 2.50, 0.6304	0.00, 0.1587, 0.50, 0.6668, 0.75, 0.5413, 1.00, 0.2319, 1.20, 0.0136, 2.50, 0.5987	-	Table of fraction dry matter partitioned to the stem (2nd column) as a function of development stage (1st column)
FSOTB	0.00, 0.0000, 0.50, 0.0000, 0.75, 0.0515, 1.00, 0.6747, 1.20, 0.9879, 2.50, 0.3422	0.00, 0.0000, 0.50, 0.0000, 0.75, 0.0332, 1.00, 0.5199, 1.20, 0.9841, 2.50, 0.3697	0.00, 0.0000, 0.50, 0.0000 0.75, 0.0592, 1.00, 0.7681, 1.20, 0.9862, 2.50, 0.4013	-	Table of fraction dry matter partitioned to the storage organs (2nd column) as a function of development stage (1st column)

[z]Refer to IRRI (2009) for all the other crop parameters of IR 72 that are not specified here
[Y]Development stages (DVS) in ORYZA (v3) are designated as follows: 0 = emergence; 0.4 = start of photoperiod-sensitive phase; 0.65 = panicle initiation; 1.0 = flowering (50%); 2.0 = physiological maturity

Appendix E. Kampong Thom Farm Management and Yield Data

Table E.1. Farmer's yield and agronomic practices of sample farms visited in Kampong Thom province.

Farm Location	Variety	N Applied (kg-ha^{-1})	Average Irrigation Depth (cm)	Planting Density (plants-m^{-2})	Harvest Yield (t-ha^{-1})
12°41'45.8"N 104°47'33.0"E	IR 5154	54_{L}	10_{M}	549_{M}	3.5
12°41'03.3"N 104°47'18.1"E	Sen Kra Ob	54_{L}	5_{L}	480_{L}	3.8
12°41'24.2"N 104°47'45.8"E	IR 5154	108_{H}	10_{M}	1177_{H}	5.0
12°41'32.0"N 104°47'39.8"E	IR 5154	-	10_{M}	677_{M}	5.5
12°41'33.2"N 104°47'04.3"E	Sen Kra Ob	64_{M}	10_{M}	567_{M}	4.0
12°41'20.1"N 104°47'27.8"E	Sen Kra Ob	54_{F}	15_{H}	659_{M}	4.0
12°39'21.3"N 104°46'57.3"E	IR 5154	110_{H}	15_{H}	1569_{H}	4.0
12°39'52.7"N 104°47'31.9"E	Sen Kra Ob	64_{M}	10_{M}	769_{M}	3.0
12°40'19.5"N 104°47'36.8"E	IR 5154	96_{H}	10_{M}	759_{M}	7.0
12°41'10.9"N 104°47'39.7"E	IR 5154	96_{H}	10_{M}	905_{M}	4.7
12°39'47.6"N 104°47'14.2"E	IR 5154	96_{H}	10_{M}	921_{M}	5.0
12°39'13.6"N 104°47'12.1"E	IR 5154	192_{H}	10_{M}	967_{M}	6.0

N applied: Low$_{L}$ (60 <), Medium$_{M}$ (≤ 60 < 90), High$_{H}$ (≤ 90)
Irrigation: Low$_{L}$ (≤ 5), Medium$_{M}$ (< 5 < 15), High$_{H}$ (≤ 15)
Planting density: Low$_{L}$ (< 500), Medium$_{M}$ (≤ 500 < 1000), High$_{H}$ (≤ 1000)

We examined the agronomic management of our 12 sample farms in Kampong Thom during the dry season of 2019. We analyzed the practices that contributed to the productivity of their harvest, disregarding biotic factors such as pests and diseases. We recorded the timing and amount of N fertilizer applied, depth of irrigation, planting density, rice variety planted, and the final harvest yield through personal interviews with farmers. We further grouped the amount of N application, intensity of irrigation, and planting density to fair, medium, and high for statistical purposes.

Using ANOVA with significance level of 0.05, we found that the amount of applied N (*p-value* = 0.045) and the variety used (*p-value* = 0.039) have significant effects on the final yield. Note, however, that there was no significant difference detected among groups of N levels after verifying with Tukey HSD. After establishing the yield gap drivers, we decided to perform yield sensitivity analysis on the IR 5154 with varying amounts of N fertilizers applied at different key development stages of rice crop.

Appendix F. Battambang Rice Production Estimation

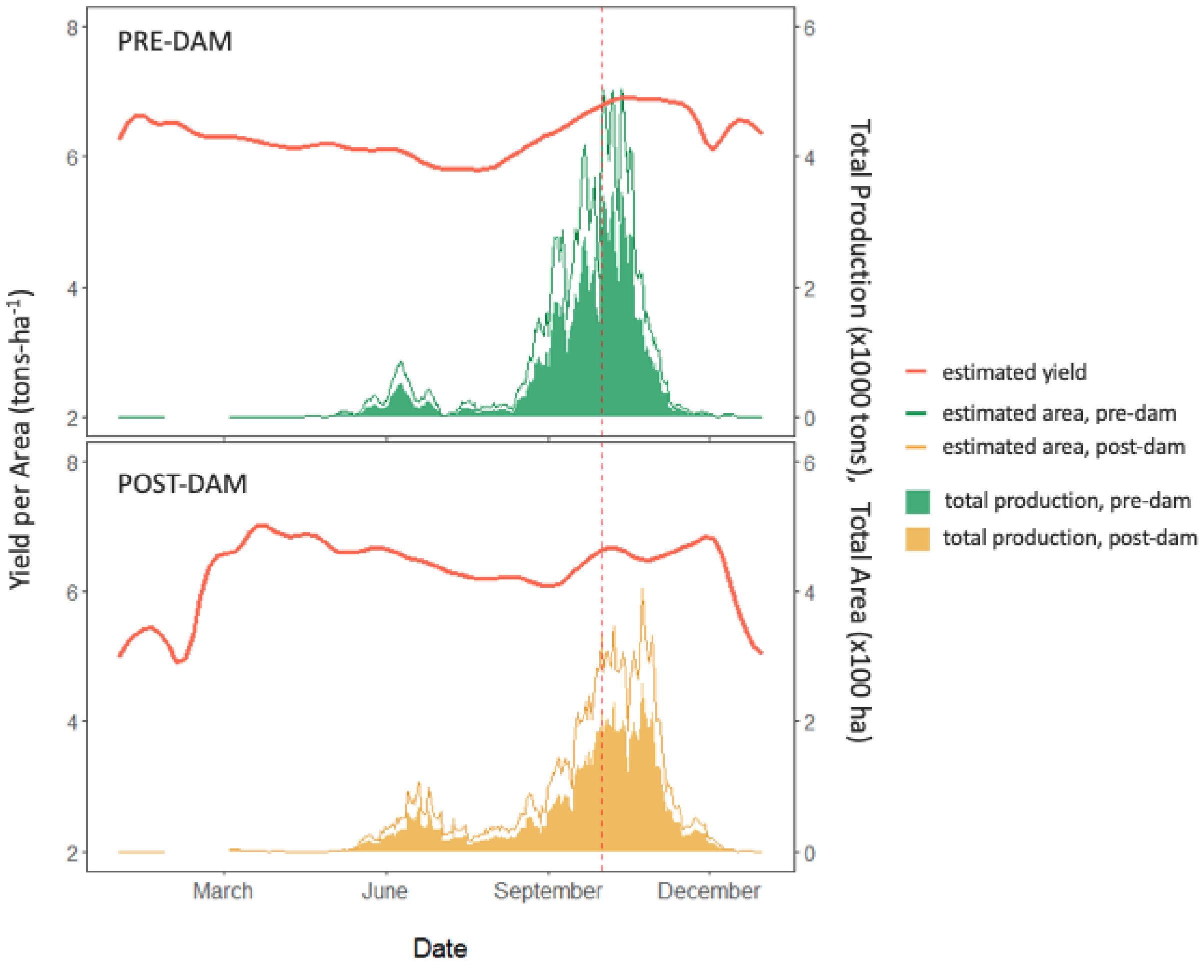

Figure F.1. Estimating the total production per day in Battambang province by multiplying the attainable yield estimated by ORYZA (v3) and the area detected by PhenoRice at pre-dam and post-dam. IR 5154 variety was used for the simulations and agronomic inputs were based on the farm practices that produced the median yield during the site visit. There was a noticeable change in the estimated yield pattern during post-dam, showing unfavorable cropping for late dry season (December to January). Total rice production at post-dam significantly decreased in November (p-value ≤ 0.01) and December (p-value ≤ 0.05).