Agriculture Risk Management Support (ARMS) for Rain-Fed Lowland Rice in Lao PDR

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PREFACE

As rain-fed rice accounts for a critical percentage of agricultural production in Laos, this rice production ecosystem could make the country vulnerable to the impacts of climatic variability and change. Failure in rain-fed rice production could have catastrophic ramifications for the economy and national food security. Together with the National Agriculture and Forestry Research Institute (NAFRI, Laos) and the International Research Institute for Climate and Society (IRI, U.S.), the APEC Climate Center developed and proposed an integrated approach to reduce climatic risk by providing tailored information in the form of an agro-climate advisory. Capacity building activities were conducted, to ensure optimized usage of the output and sustained benefits for the country, in relevant institutions such as the Department of Meteorology and Hydrology (DMH, Laos), NAFRI, as well as for local farmers.

According to the complexity of the crop models, attainable yields under no-stress conditions can be predicted, and detailed agricultural management information can be assessed to determine best management practices to achieve the target rice yields. We expect that based on the results from the first year, this study can become useful for the reduction of the climate-related risks in rain-fed lowland rice production ecosystems in Laos, as well as for the improvement in livelihoods of the rural people of Laos, and subsequently food security enhancement in Laos.

I would like to give special thanks to Dr. Jong Ahn Chun from APCC, who has served as the Principal Investigator for this project. I am also grateful to Dr. Daeha Kim, Ms. Eunjeong Lee, and Ms. Christianne Aikins from APCC. In addition, I would like to thank Drs. W. Baethgen, S. Mason, A. Robertson, C. Kelly, and E. Han from

IRI for providing detailed relationships between climate and rice productivity. My sincere thanks also goes to Director Myeong-Cheoul Cho from the KOPIA Laos Center, Deputy Director General Vanthong Phengvichit and Dr. Thavone Inthavong from NAFRI, and Ms. Phetluangsy and Mr. Manivong from DMH in Lao PDR for their support throughout this project.

Dr. Hong-Sang Jung
Executive Director
APEC Climate Center
March 2018

EXECUTIVE SUMMARY

Overview of the Project

Rain-fed rice accounts for a critical percentage of agricultural production in Laos, making the country vulnerable to the impacts of climatic variability and change; a failure in rain-fed rice could have catastrophic ramifications for the economy and national food security. However, this reliance on rain-fed rice also provides an opportunity to build impactful agricultural resilience through a highly specialized project. To reduce climactic risk, this project integrated historical weather data and sophisticated climate forecasts with locally-calibrated agricultural models to provide tailored information that shows agro-climate advisory. This approach is followed by capacity building activities among relevant institutions, such as the Department of Meteorology and Hydrology (DMH, Laos) and the National Agriculture and Forestry Research Institute (NAFRI, Laos), as well as local farmers, to ensure optimized usage of the output and sustained benefits for the country. The project involved international collaboration with the APEC Climate Center (APCC, Republic of Korea), the NAFRI, and the International Research Institute for Climate and Society (IRI, U.S.). In particular, this project has five major tasks: (1) tailoring seasonal to sub-seasonal climate forecasts to Laos and the target area; (2) producing distributed precipitation data at a high resolution; (3) translating climate forecasts to agricultural information and evaluating benefits of forecast-based agricultural decision making; (4) developing a mobile application for agro-climate advisory, based on seasonal to sub-seasonal climate forecasts; and (5) stakeholder engagement and training.

Local stakeholders will be consulted and engaged throughout the project to identify needs and develop a practical output, helping to ensure relevance and sustainability. These five major tasks are planned to be conducted in two years (2017.1.1.–2018.12.31). The findings of this study will be reflected to the activities of the second year which ultimately aims to develop a semi-operational agricultural climate risk management system in collaboration with the APCC, DMH and NAFRI (Figure 1).

Materials and Method

Figure 1 depicts the major partner institutions involved in this study. In this report, we present on the first year tasks and their results. We attempted to compare three crop models (AquaCrop, EPIC, and CERES-Rice) for five rice cultivars (TDK1, RD10, RD4, Kodeo, and TSN2) in wet season lowland rice production systems in Laos. For this comparison, the three models were calibrated and validated for the five rice cultivars with the observed rice phenological data, agricultural management practices, and rice yields collected form the rain-fed lowland rice environment in Savannakhet Province. This study region is located in the lower central agricultural regions of Laos (15.833 – 17.167 °N, 104.667 – 106.833 °E). The remotely sensed vegetation status (e.g., NDVI/EVI or LAI) at critical crop growth stages were also assessed as a good indicator of crop yields at harvest. These results will be used to establish crop yield outlooks next year.

The predictability of rainfall statistics around monsoon onset and of onset date over Laos was analyzed based on seasonal and sub-seasonal (S2S) forecast models in this study. We defined onset date here as the first wet day of the first seven-day wet spell, not followed by a long dry spell. The APHRODITE rainfall dataset (daily, 0.5 by 0.25° degree resolution, 1951–2007) was used to determine seasonal (MMJASO) rainfall and rainfall onset date for Savannakhet (represented by a box encompassing the 16.375 – 16.875 °N, 104.625 – 105.125 °E). We investigated various variables including geopotential height, specific humidity, zonal and meridional wind, and vertical velocity at three atmospheric pressure levels (850 hPa, 500 hPa, and 250 hPa).

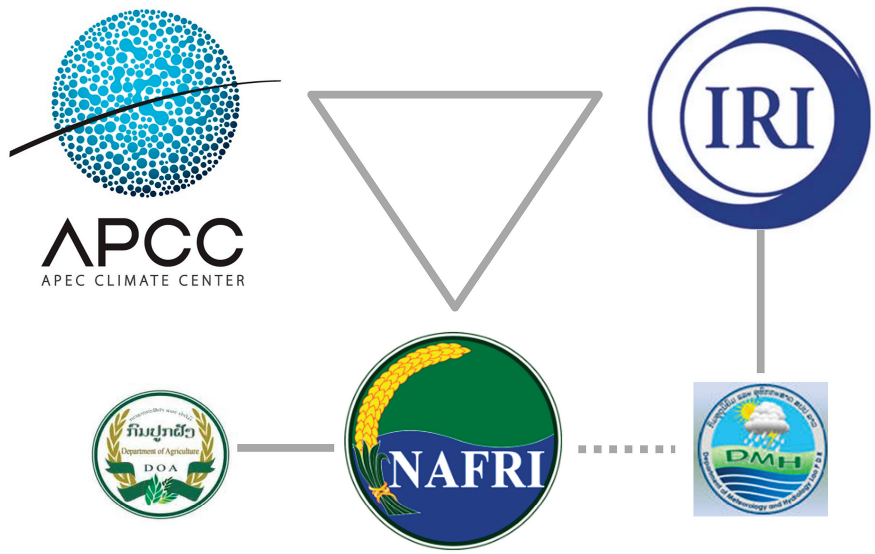

Figure 1. Partner organizations and project framework. APCC: APEC Climate Center (Republic of Korea), IRI: International Research Institute for Climate and Society (U.S.), NAFRI: National Agriculture and Forestry Research Institute (Lao PDR), DMH: Department of Meteorology and Hydrology (Lao PDR), DOA: Department of Agriculture (Lao PDR).

Results and Discussion

The three crop models (AquaCrop, EPIC, and CERES-Rice) were used to simulate rice yields in wet-season lowland rice production environment in Savannakhet province and the responses of climatic variables and agricultural managements to rice yields were compared in this study. The simulation results of those models showed that the EPIC model slightly underestimated in 2007 and overestimated in 2008, while the AquaCrop and CERES-Rice models slightly overestimated the rice yields in both years. A further study on experiments with no water and nutrient stresses for rice yield is suggested to accurately calibrate those process-based crop models. The values of goodness-of-fit measures for those three crop models lead us to believe that the AquaCrop model better performs than the other two crop models. However, it should be noted that the AquaCrop model might not be an adequate model to assess detailed agricultural management information, considered as best management practices to reduce climate-related risks on rice productivity.

The results from the predictability of onset date for the Savannakhet region indicate that the regional geopotential height and specific humidity fields in particular have the potential to be used operationally to improve the predictability of total seasonal rainfall as well as late monsoon onset (post April 25). The potential was higher especially when these variables were used in conjunction with changes in the regional circulation (prevailing wind field). We investigated the potential of climate variables as an indicator of rice yield outlook. The findings from the investigation showed that the relationship is sensitive to definitions of onset dates. In Savannakhet, rainfall amount and frequency in vegetative stages (MJJ) positively affected the rice yields, while negatively in late growing season. Dry spell showed opposite results: positive correlation in reproductive and ripening stages (ASO) and negative correlation in vegetative stages. From the investigation of the value of monitored vegetation information from satellite for crop yield outlook, we found that in general EVI was more useful than NDVI in predicting yields.

Conclusions

The Laos economy will benefit from continued legislation, policy measures, and capital investment to support the agricultural sector, which is a key sector for establishing sustainable and inclusive economic growth, particularly in the early stages of economic development. The findings in this paper suggest that a simple crop model like the AquaCrop model can be useful to predict attainable yields under no stress conditions (i.e., water, fertility, and salinity stresses), and that a more complex crop model like the CERES-Rice model can be useful to assess detailed agricultural management information to determine best management practices for the achievement of the targeting rice yields. The findings from this study indicate that skillful S2S forecast at different rice growing stages would be able to serve as in indirect indicator for rice yield outlook. We concluded that based on these first year results, this study can be useful for the reduction of the climate-related risk managements in rain-fed lowland rice production ecosystems in Laos and for the improvement of the livelihood of the rural people of Laos, and subsequently for the enhancement of food security in Laos.

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Chapter 1.

Predictability Assessment of Monsoon Onset Date over Laos, Based on Seasonal and Sub-Seasonal Forecast Models

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ABSTRACT

More reliable risk management frameworks to enhance preparedness and resilience to climate variability are required for rain-fed lowland rice in Lao PDR. This study aims to develop a framework by adopting three critical factors: developing more reliable seasonal climate information; translating climate or available information to agriculturally relevant information, and; building capacity of local stakeholders who will play a key role in sustaining the system. First, the predictability of monsoon onset date and seasonal rainfall was explored. The results from the Savannakhet region indicate that the regional geopotential height and specific humidity fields in particular, especially when used in conjunction with changes in the regional circulation (prevailing wind field) have the potential to be used operationally to improve predictability of total seasonal rainfall as well as late monsoon onset (post April 25), from the beginning of March. A high (2 arc-minute) resolution gridded rainfall product was produced by merging CHIRPS global rainfall data and 15 weather station data. The potential of climate variables as an indicator of rice yield outlook was investigated. The analysis on relationship between monsoon onset dates and rice yields showed that monsoon onset date should be carefully defined in agricultural context, not following to typical definition based on atmospheric condition. Geographical characteristics also affect the correlation between monsoon onset and rice yields. Next, we examined the relationships between rainfall (amount, frequency and dry spell) at

multiple time scales (one to six months) and rice yields. In Savannakhet, rainfall amount and frequency during the vegetative stages (MJJ) positively affected the rice yields, while effecting it negatively during the late growing season. Dry spell showed opposite results: a positive correlation during the reproductive and ripening stages (ASO) and a negative correlation during the vegetative stages. This finding indicates that skillful S2S forecast at different rice growing stages would be able to serve as in indirect indicator for rice yield outlook. Vegetation information from satellite data (MODIS 250 m resolution) has a potential for crop yield outlook, but high uncertainty in the data requires careful approach in applying the simple relationships for operational purposes in collaboration with APCC, DMH and NAFRI.

1.1 INTRODUCTION

Lao PDR (Laos) is a landlocked country sharing its borders with Myanmar, Cambodia, China, Thailand, and Vietnam. Approximately 6.8 million people live in its 18 provinces and 63% of them live in rural areas (UNDP, 2015). Laos is very mountainous, and fertile lands with high agricultural productivity are found along the Mekong plains. Despite steady economic growth in the 21st century, Lao PDR remains a least developed and low-income food-deficit country, ranking 139th out of 187 countries on the 2014 Human Development Index (Malik, 2014) and 61st out of 76 countries (von Grebmer et al., 2014) on the 2014 Global Hunger Index. Approximately one-quarter of the population lives in poverty, mostly in rural and remote regions (WFP, 2013).

In Laos, agricultural production plays a crucial role in the national economy since it engages more than 80% of population (OECD, 2014). Rain-fed agriculture, which is highly vulnerable to climatic variability, accounts for a significant portion of the gross domestic production, and thus affects people's livelihoods. Climatic variability is a critical concern of farmers in Laos, and precipitation in rainy seasons is particularly a keen interest of stakeholders. It is reported that abnormal weather patterns have affected agricultural productivity and listed climatic changes (e.g., delayed monsoon onsets, prolonged dry periods in rainy seasons and increasing flash floods) as factors that lead to food insecurity. There is a critical need of developing management strategies for mitigating climatic risks that provide actionable information for stakeholders and assist decision-makers in assessing risks of near-term climatic variability. It may include prioritization of planning and investment efforts that protect farming communities from high vulnerability to climatic changes.

To this end, seasonal and sub-seasonal (S2S) climate forecasts can be valuable information. S2S climate forecasts with high reliability can be useful for supporting pre-season decisions (e.g., on crop selections and planting dates) and within-season policy (e.g., yield loss prediction and preparing contingency plans). The use of climate forecasts for making agricultural decisions has provided practical advantages to several countries in the tropical zone (Shafiee-Jood et al., 2014).

Laos is also located in a region in which S2S climate forecasts show promising skills and can be improved. A tool to provide agro-climate advisory based on S2S climate forecasts may provide efficacious adaptation strategies for Laos and subsequently contribute to the improvement of the agricultural productivity in Laos.

This study is based on the proposition that effective climate risk management in rain-fed lowland rice production relies on three critical factors: more reliable seasonal climate information, tools to generate agriculturally relevant information and building capacity to utilize that available information. The overarching goal of this project is to enhance the capacity of agricultural sectors in Lao PDR, particularly for rain-fed lowland rice at the risk of high climatic variability. Specific objectives includes: 1) investigating more reliable S2S climate forecast, 2) supporting establishment of agro-climate outlook for rain-fed rice by exploring available climatic and agricultural data, and 3) building capacity of human resources at relevant institutes (Department of Meteorology and Hydrology, and National Agriculture and Forestry Research Institute) for a sustainable management of the proposed system in the project.

First, we explored possible ways to improve seasonal and sub-seasonal climate forecasts for Lao PDR. Untimely monsoon onset is reported as a major obstacle for rain-fed rice production in the wet season. More accurate prediction of the monsoon onset is expected to benefit farmers in scheduling management practices such as land preparation, sowing and transplanting. Secondly, we produced distributed precipitation data at a high resolution (2 arc-minute) by merging ground station data and the Climate Hazards group Infrared Precipitation with Stations (CHIRPS) global rainfall. This distributed precipitation products are expected to contribute hydrologic and agronomic applications in data-sparse regions in Laos. Third, we assessed the utility of climate forecasts for establishing crop yield outlooks by analyzing the relationship between climate variables at different crop growth stages with crop yields. In addition, value of monitored vegetation information as an indicator of crop yields at harvest was examined. Lastly, extension agents or agricultural advisors are to be trained so that they can use the improved information, how to interpret it and make appropriate recommendations to farmers.

Building capacity of relevant government agencies or institutions as well as successful integration of climate and agricultural information into decision making will lead to improve resilience of rice farming in Lao PDR to the climate variability and change.

1.2 DATA AND METHODOLOGY

1.2.1 Study Area

Lao PDR is located in the center of the Southeast Asian peninsula and surrounded by Myanmar, Cambodia, China, Thailand, and Vietnam. Rice has been a top priority for the Government of the Lao PDR and National development policies and strategies have emphasized the importance of rice in achieving food security and stimulating economic grow. The increase in national rice production has been driven by four central provinces (Savannakhet, Khammuane, Vientiane and Vientiane Capital) and one province (Saravan) in the south. It is estimated that the Government of the Lao PDR's seven reference plains (the five provinces above with the inclusion of Borikhamxay province in the center and Champasack and Attapeu provinces in the south) accounted for more than 80 percent of the country's rice production expansion between 1995 and 2010 (Eliste et al. 2012). Figure 1.1 shows the estimated rice growing areas in Lao PDRD in 2008-2008.

For the climate analysis for predictability of S2S forecast, we will explore climate data for the entire country. However, this study mainly focused on rain-fed lowland rice farming areas in Savannakhet Province (red in Figure 1.1). The Savannakhet Province accounted for 23% of total lowland rice areas in the country as of 2004, which is the largest portion compared to other provinces (Inthavong et al. 2012). Chronic drought has been the major risk for rain-fed lowland rice farming in the wet season in the Savannakhet Province (Inthavong et al. 2012) and thus intensive field surveys and studies on the impact of water availability and soil characteristics have been conducted in the past (Inthavong et al. 2011a; Inthavong et al. 2011b, 2012; Inthavong et al. 2014)

Monsoonal climate is dominant in the target area with two distinct seasons: wet (May to October) and dry (November to April). Almost 90% of annual rainfall occurs in the wet season. According to the records from 1985 to 2004, August is the wettest month with an average of 354 mm ranging from 131 to 565 mm (Inthavong et al. 2012). Mean annual rainfall varies within the province from 1300 mm (northwestern area) to 1800 mm (south and northeastern areas) (Inthavong et al. 2011a).

Since the eastern part of the province is covered by deciduous dipterocarp forest, rice is grown mostly in the central and western parts of the province. Most of the farmers in the area sow seeds in the nursery in late April to May depending on the monsoon onset, but the onset can be delayed until as late as June, as in 2014 (IRI 2015). According to the data from the Soil Survey and Land Classification Centre (SSLCC) of Laos, more than 80% of the agricultural area in the province is classified as soils with low clay content: most of the rice paddy fields have less than 12% clay content.

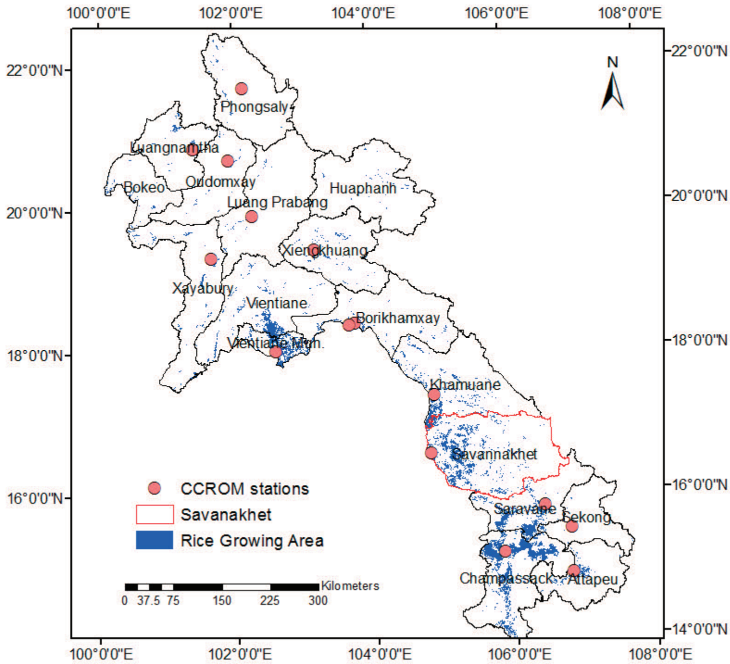


Figure 1.1. Rice growing areas in Lao PDR in 2007-2008

1.2.2 Data and Methodology

1.2.2.1 Precipitation

We explored a range of rainfall products including APHRODITE (V1101R1), CHIRPS and PERSIANN as well as CCROM station data. APHRODITE is a daily gridded precipitation dataset created by analyzing rain gauge observation data across Asia through the activities of the Asian Precipitation—Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE) project (Yatagai et al. 2012). The APHRODITE product is provided in 0.5° and 0.25° resolution for a period of 1951 to 2007 over Monsoon Asia. The gridded precipitation is derived from original rain-gauge data, precompiled datasets, and global telecommunication system reports and accessible through IRI's website (http://iridl.ldeo.columbia.edu/SOURCES/.RIHN/.aphrodite/.V1101/) or via http://www.chikyu.ac.jp/precip/english/products.html.

The Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset is a quasi-global rainfall dataset available from 1981 to near-present. The CHIRPS incorporates 0.05° resolution satellite imagery with in-situ station data (Funk et al. 2015). The data is accessible through http://iridl.ldeo.columbia.edu/SOURCES/.UCSB/.CHIRPS/.v2p0/ or http://chg.geog.ucsb.edu/data/chirps/.

Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks Climate Data Record (PERSIANN-CDR) is a retrospective satellite-based precipitation dataset which provides daily and 0.25° rainfall estimates for the quasi globe (60 °S-60 °N) for the period of 1983 to near present (Ashouri et al. 2015; Sorooshian et al. 2014). The data is accessible through https://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCDC/.CDR/.PERSIANN/.v01r01/?Set-Language=en or http://chrsdata.eng.uci.edu/.

Daily weather (precipitation, maximum and minimum air temperature) from ground weather stations are available through Centre for Climate Risk and Opportunity Management in Southeast Asia Pacific (CCROM) 15 stations in Lao PDR for the period of 1980-2010. The location of the stations is shown in Figure 1.1 and the data is accessible via. http://iridl.ldeo.columbia.edu/-SOURCES/.CCROM/.Lao/.stations/. Note that only a few of the stations have the full 30 years of data as shown in Figure 1.2.

1.2.2.2. Methodology for predictability of seasonal rainfall and onset date

The APHRODITE rainfall dataset (daily, 0.5° and 0.25° resolutions, 1951-2007) was used to determine the seasonal (MMJASO) rainfall and rainfall onset date for

Savannakhet (represented by a box encompassing the 16.375 - 16.875 °N, 104.625 - 105.125 °E). The area-mean timeseries of total rainfall and onset date for the MJJASO seasons were standardized and the resulting values were categorized as either above normal (greater than one standard deviation above the mean), below normal (more than one standard deviation below the mean), or normal (between +/- one standard deviation). These indices were used to construct composites of atmospheric variables for the greater Laos region using the ERA Interim reanalysis (2° by 2° spatial resolution). The examined variables included geopotential height, specific humidity, zonal and meridional wind, and vertical velocity at three atmospheric pressure levels (850 hPA, 500 hPa, and 250 hPa). Means were then calculated over similar years, based on the indices mentioned above, to represent atmospheric conditions typically present during wet, normal or dry years in the seasonal rainfall case, and during early (more than one standard deviation below the mean, or Mar 1-Mar 21), normal (Mar 21-Apr 25) or late (greater than one standard deviation above the mean, or after Apr 25) onset years. Onset date was here defined as the first wet day of the first seven-day wet spell, not followed by a long dry spell. In this case the atmospheric anomalies present during the individual months of March, April and May were calculated in order to examine lead times for seasonal onset dates and to determine the potential for improved predictability.

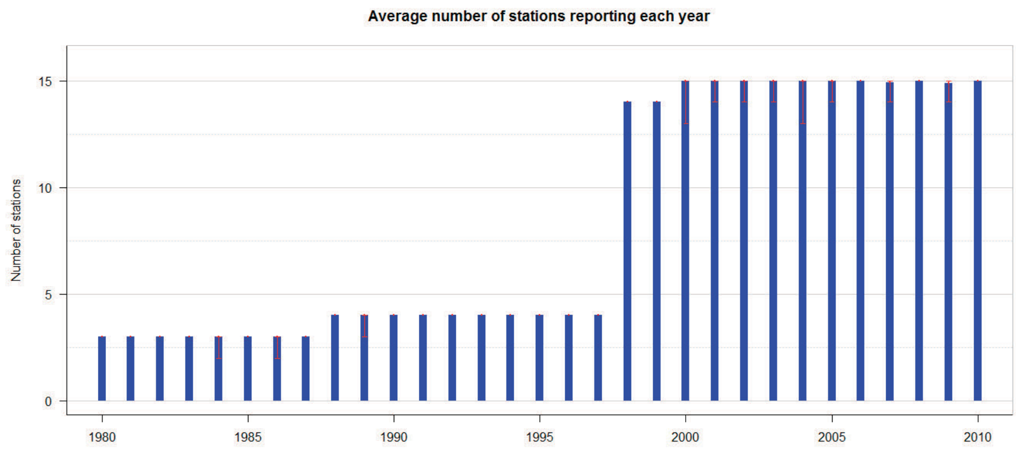


Figure 1.2. Data availability of CCROM rainfall station data.

1.2.2.3 Agronomic data

Rice yield data from two different sources were used to find relationships between climatic variables or vegetation indices and yields. First, province-level rice yield data from 18 provinces for the period 1975-2014 were obtained from the Department of Agricultural in Lao PDR. Note that the yield data has many missing years as shown in Figure 1.3. In addition, over the last 20 years (1991-2011), Lao rice production has increased considerably mainly due to adoption of improved rice varieties, investment in irrigation and expansion in rice growing areas, particularly in the central and southern lowland production areas (Eliste et al. 2012). In order to avoid the impacts of technological improvement (i.e., new rice varieties) we removed the linear trend from the historical rice yields. The linear trend was estimated by a linear least-squares regression equation for each province separately. For example, in the case of Savannakhet province, the linear trend was calculated using the equation, Yield_{pred} [ton/ha] = 0.05556 × Y_index + 1.743, where Y_index indicates a count from the reference year (i.e. 1976). For instance, Y_index = 39 is used to compute detrended yield for the year 2014. Figure 1.3 (b) shows the detrended rice yields.

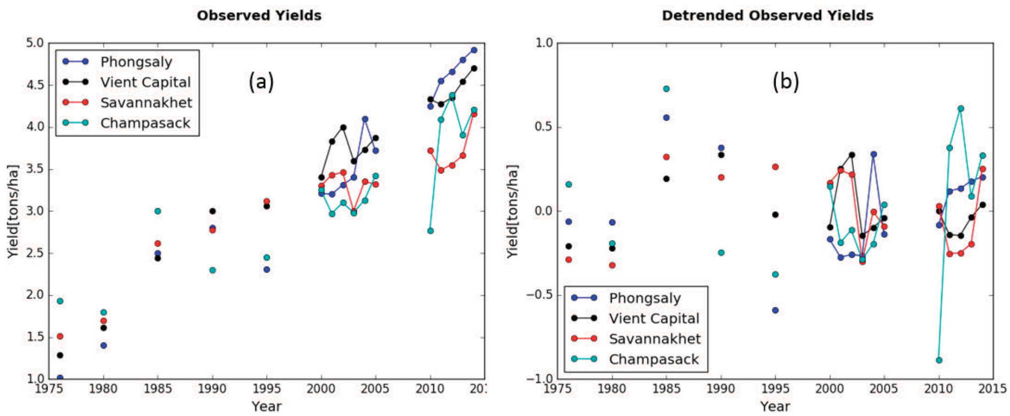


Figure 1.3. Provincial level rice yield production in selected provinces: (a) reported yield and (b) detrended yield.

Rice yield and field experimental data (dates for sowing, transplanting, flowering and harvesting, and fertilizer application etc.) at village level in Savannakhet province were collected from NAFRI. A total of 97 and 47 yield values are available for 2007 and 2008, respectively, as shown in Figure 1.4. Annual yields in Savannakhet showed similar trends and magnitudes to national yield statistics from FAOSTAT (http://www.fao.org/faostat/en/#country/120), but the observed yields collected by NAFRI in 2007-2008 are much lower than the national yield from FAOSTAT (not shown). For example, the average yields from the 2007 experimental sites are 2183 kg/ha with a standard deviation of 704 kg/ha, while the reported yield from FAOSTAT is 3723 kg/ha.

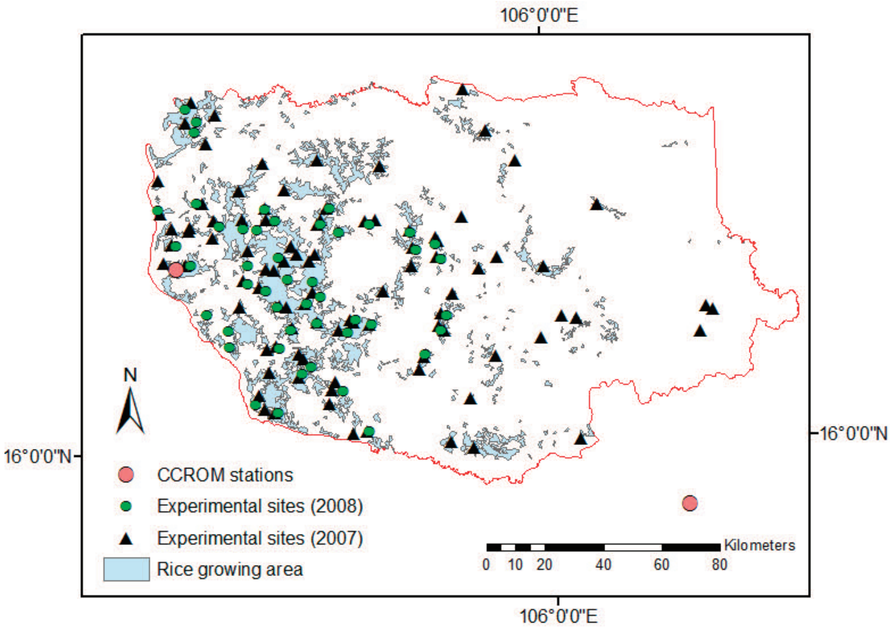


Figure 1.4. Locations of field observations in 2007 and 2008

1.2.2.4 Remotely sensed vegetation information

In order to assess the ability to establish crop yield outlooks only with monitored vegetation information (without any modeling or climate forecast information), we used two MODIS (Moderate Resolution Imaging Spectroradiometer) vegetation indices: Normalized Difference Vegetation Index (NDVI) and the Enhanced

Vegetation Index (EVI). The MOD13Q1 Version 6 product at 250 m resolution and 16-day compositing periods was obtained from a NASA Earthdata search (https://search.earthdata.nasa.gov/search?q=MOD13Q1+V006). The NDVI is chlorophyll sensitive, whilst the EVI is more responsive to canopy structural variations and has improved sensitivity over high biomass regions (Huete et al. 2002). MODIS 250 m 16-day data (MOD13Q1) is available from 2000 to near-present.

1.3 RESEARCH RESULTS

1.3.1 Assess Predictability of Rainfall Statistics Around Monsoon Onset and of Onset Date over Laos

1.3.1.1 The seasonal cycle of precipitation and temperature over Laos

The climatological seasonal cycle of precipitation and temperature at a gridpoint in the project region [105.0 - 105.5 °E, 16.5 - 17.0 °N] is shown in Figure 1.5, plotted from the IRI's "Select-a-Point Climatology" maproom[1]. This maproom allows the user to select any point of interest, which can be especially valuable for training purposes, so as to set the scene and select the relevant season for in-depth analysis. Figure 1.5 shows that the summer wet season begins during the April-June months. Mean temperatures reach their maxima during these months, while the diurnal range decreases during the rainfall season due to cloud cover.

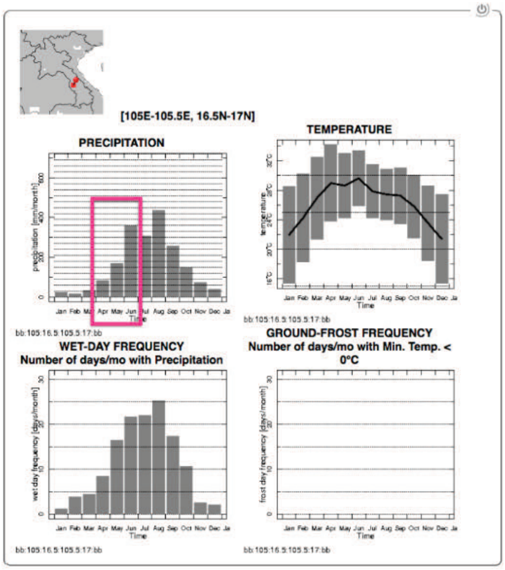


Figure 1.5. Climatological mean seasonal cycle of precipitation and temperature, computed from University of East Anglia Climatic Research Unit TS2.1 monthly data set on a 0.5° lat/lon grid, at the [105.0 - 105.5 °E, 16.5 - 17.0 °N]. The bars in the temperature plot indicate the diurnal range. From the IRI's "Select-a-Point Climatology" maproom[1].

1) http://iridl.ldeo.columbia.edu/maproom/Global/Climatologies/Select_a_Point.html

Having identified the onset season, we have calculated the rainy season onset date in each year from using an agronomic definition, as the first day of the first significant wet spell, not followed by a long dry spell. Figure 1.6 shows maps of the multi-year average of the onset date, computed from 3 different global gridded datasets: the Aphrodite gauge-based data; the PERSIANN satellite-based product; and the CHIRPS which is based on both satellite and gauge data. The definition for onset used here is, for each year from March 1st and within the next 90 days, the first wet day (greater than 0 mm) within the first 5-day running window that totals 20 mm or more of precipitation and with at least 1 wet day and that is not followed by one 7-day dry spell within the 21 days following the finding of an onset date.

The maps in Figure 1.6 exhibit common features, with the monsoon onset occurring during late March (blue color) in the Gulf of Thailand, and in April-May over Laos. However, there are also some significant differences regionally between the estimates obtained from different products that require more investigation, and comparison against station data. For example, near the location [105 °E, 15 °N], the Aphrodite and CHIRPS indicate a mean onset date in May, compared to April in the PERSIANN data.

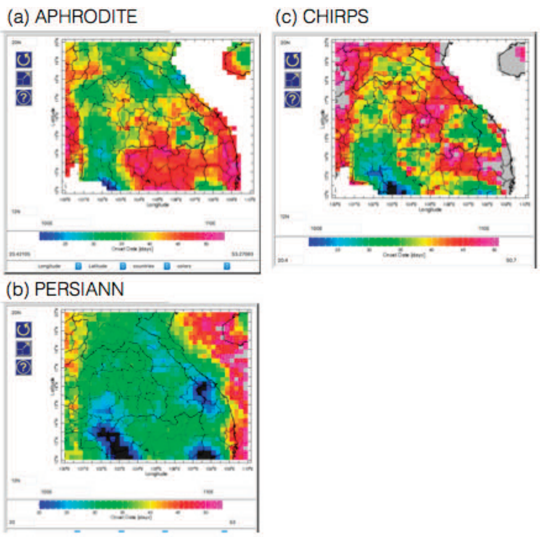


Figure 1.6. Maps of climatological average onset date, calculated from three different gridded daily precipitation datasets. Colors denote the onset day, beginning on March 1.

1.3.1.2 Comparison of various rainfall products over Laos

We compared five rainfall datasets: Aphrodite, CCROM, CHIRPS, PERSIANN and monthly precipitation (approximately 30 years of data) from 10 weather stations in Lao PDR. Annual (for the MJJASO season) time series of the area mean of greater Laos (includes a portion of neighboring countries) was constructed to get a sense of how well they agree during the period of overlap. The primary findings are as follows:

1) All five time series are reasonably correlated over the period of overlap (1982-2008).
2) There appears to be a slight dry bias in the Aphrodite data, which is the only dataset that extends before 1980 (back to 1950).
3) There are quite a few missing values in the CCROM stations prior to 2000.
4) The CHIRPS data (merged station/satellite) are almost identical to the PERSIANN data (satellite), which seems to indicate that the CHIRPS data are relying more heavily on the satellite data than the station data.
5) The monthly stations from Lao PDR agree well with the CCROM stations and include two stations that are not in the CCROM dataset. Some of the stations extend back to 1950 whereas the CCROM stations (daily) do not.

Therefore, for purposes of preliminary investigation of monsoon onset predictability we proceed using the APHRODITE data.

1.3.1.3 Predictability of onset date from atmospheric conditions

Area-mean timeseries were used to determine seasonal (MMJASO) total rainfall and rainfall onset date (beginning from March 1) for Savannakhet. The timeseries were standardized and indices were constructed for above normal, below normal, or normal total seasonal rainfall, and for late, early and normal onset dates in March, April and May. These indices were used to construct composites of 850hPa pressure level geopotential height and specific humidity for the regional circulation around and including Lao PDR by taking the means over similar years, based on the aforementioned indices. March, April and May were selected in order to examine lead times for seasonal onset dates and to assess the potential for improved predictability.

Results are shown in Figure 1.7 and Figure 1.8 for composites of total seasonal rainfall (Figure 1.7) and for onset dates for March, April and May respectively (Figure 1.8). In Figure 1.7 (a) we see that during drier-than-usual monsoon seasons the low-level geopotential heights are higher than usual, indicating higher surface pressure and therefore reduced convection and rainfall. Additionally, we can see in Figure 1.7 (b) that the lower-level specific humidity is reduced, particularly to the east over the South China Sea, thereby reducing the moisture source for rainfall in the region. Figure 1.7 empirically demonstrates the clear and well-established relationship between these two variables and seasonal rainfall. This further implies that these variables also have the potential to be used as predictors of subseasonal rainfall metrics such as onset date.

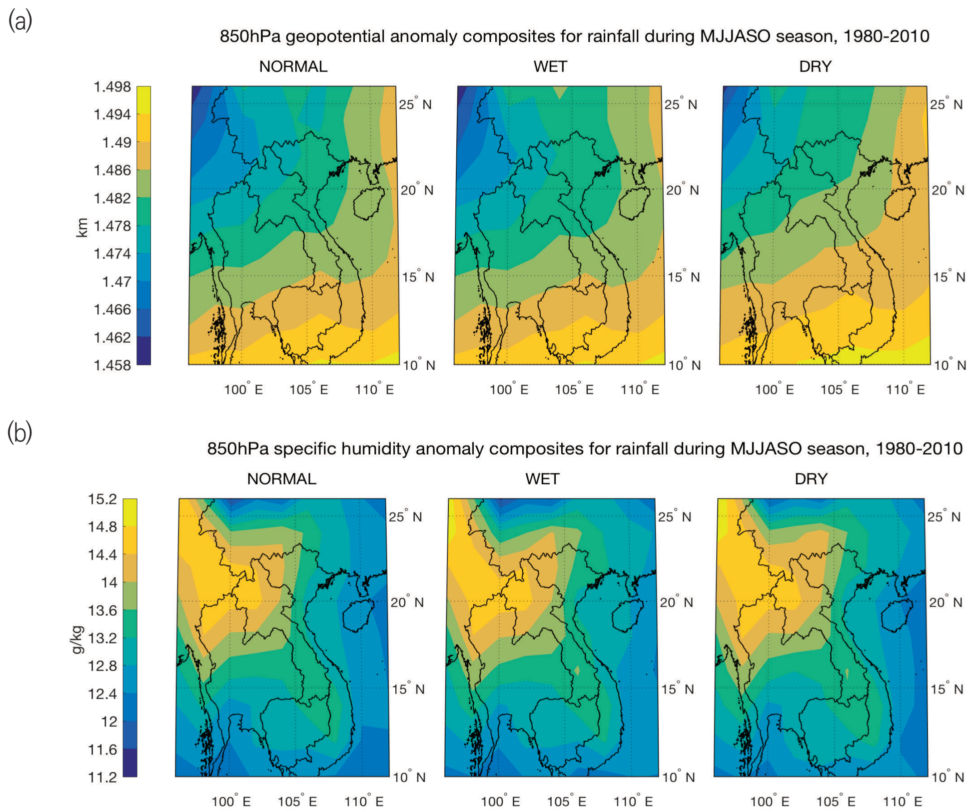


Figure 1.7. Composites of ERA Interim 850hPa geopotential height and specific humidity during normal, wet and dry years, based on Aphrodite rainfall over the MJJASO season.

In Figure 1.8 (a) (b) (c) we show the geopotential height results for composites of normal, early and late monsoon onsets for the months of March, April and May, respectively. We can see a stronger than usual geopotential height gradient from the northwest to the southeast along with accompanying higher surface pressure in Lao PDR during March and progressing through May during late onset years. The patterns represent a shift in the magnitude and direction of the lower-level winds that clearly distinguishes them from the patterns associated with typical normal or early onset years by affecting the moisture advection into the area. In addition to this empirical assessment we quantitatively compared the normal and late onset patterns using a Kolmogorov-Smirnov (K-S) test, which tests the null hypothesis that the two vectors (patterns) are from the same continuous distribution. The alternative is that the two patterns are from different continuous distributions. This test revealed that when the normal and late onset patterns were compared they were found to be significantly different based on confidence intervals of $p = 0.98$, $p = 0.93$ and $p = 0.93$ for March, April and May respectively, affirming what we see qualitatively in the patterns. This clear difference in the patterns provides evidence that this variable could offer some degree of predictability of onset date.

Figure 1.8 (d) (e) (f) panels appear to indicate a reduction in specific humidity during April of late onset years, but little indication during March and May of an impending late onset. This is also reflected in the K-S tests, in which the threshold of significance for April is $p = 0.77$. Although the statistical significance for April is not as robust in the patterns as a whole as seen with geopotential height, and even less so for Mar and May, the clear difference in April available moisture over Lao PDR itself during normal and late onset years still has some potential to be used in conjunction with other variables, such as geopotential height, to incrementally increase the predictability of a late onset year, over using sea surface temperatures alone for example.

To further analyze subseasonal predictability we explored models from the North American Multi-Model Ensemble (NMME) as predictors of the monsoon onset. We examined the relationship between modeled rainfall from the CFS version 2 model (via https://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/.NCEP-CFSv2/), initialized in March, and Aphrodite rainfall for Savannakhet during March, using linear regression in the Climate Predictability Tool. We found the relationship to be very weak (a goodness index of only -0.015), indicating that this model is not a reliable predictor of March rainfall or onset in this subregion. We also used the ECMWF model in conjunction with an index of CHIRPS rainfall for Savannakhet to assess whether this model is able to capture the rainfall anomalies at lead times of one to four weeks. During the core of the 2017 monsoon (July 10-16) the ECMWF was able to forecast anomalously wet conditions (compared to the same week in previous years). Our results show the need to assess other models of the NMME.

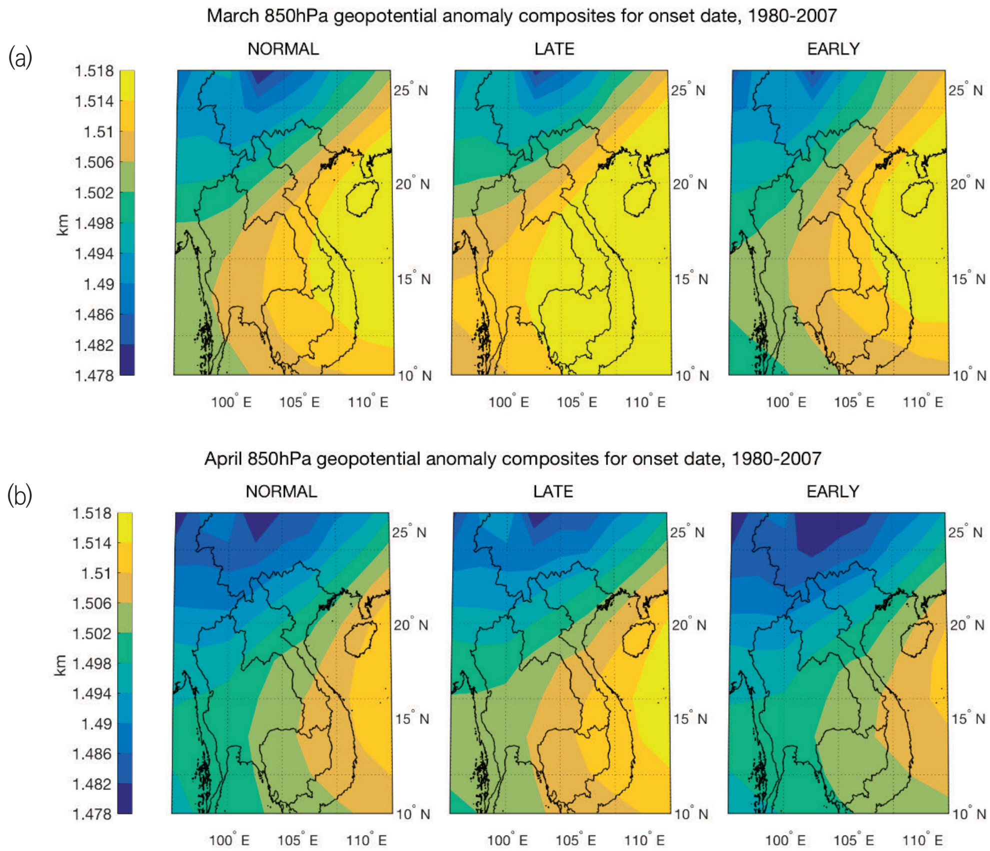


Figure 1.8. Composites of ERA Interim 850hPa geopotential height and specific humidity during normal, late onset and early onset years, based on Aphrodite rainfall.

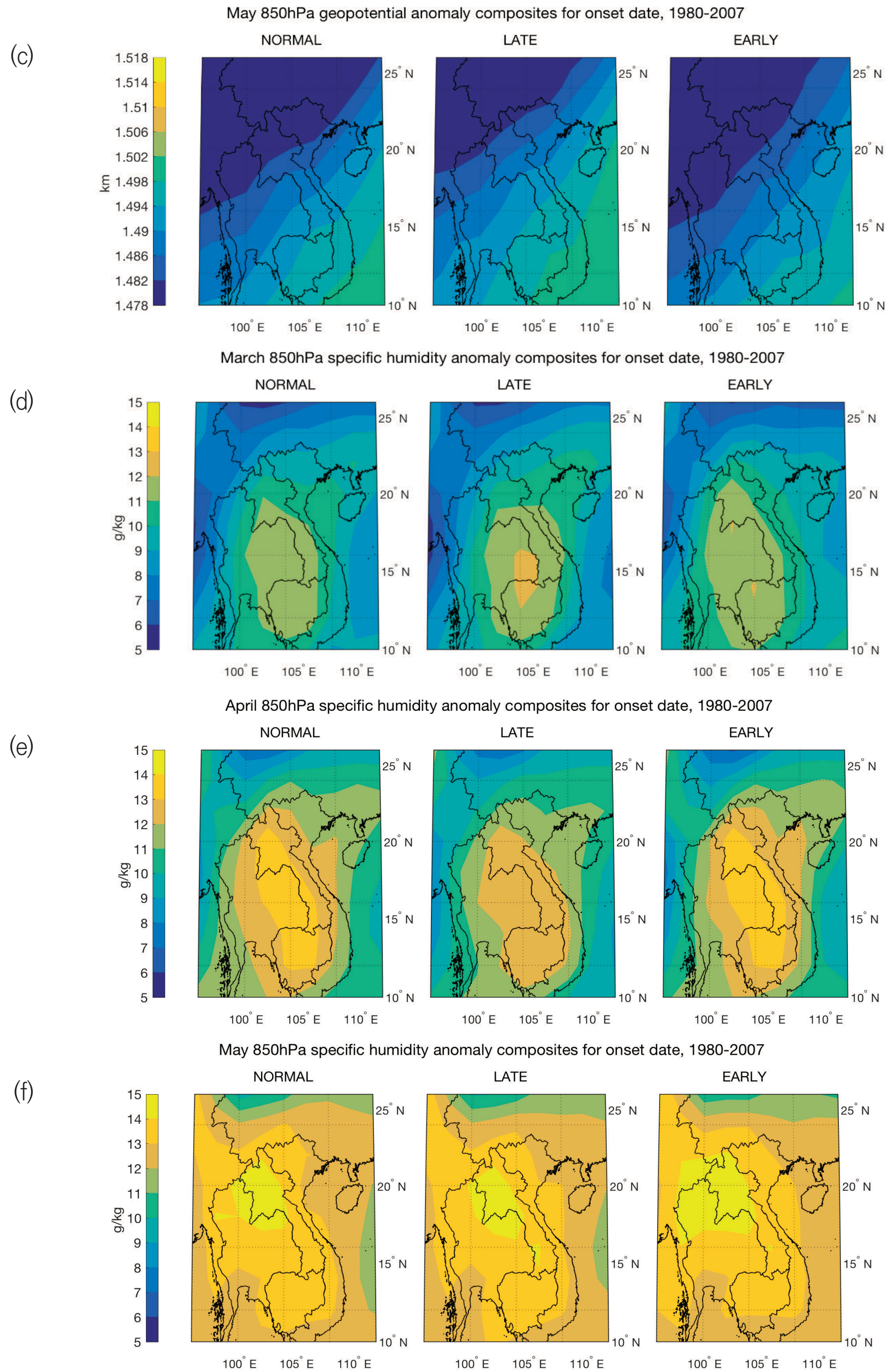


Figure 1.8. Composites of ERA Interim 850hPa geopotential height and specific humidity during normal, late onset and early onset years, based on Aphrodite rainfall. (continued)

1.3.2 Producing Distributed Precipitation Data at a High Resolution

Given the sparse climate-observation network in Lao PDR, producing spatially distributed climatic data with acceptable reliability would be a prerequisite for supporting agricultural decision-making at multiple locations. These days, there are many global gridded rainfall estimates available through satellite observations, interpolation of station data or combination of them. Even though satellite-based rainfall products have been served as an alternative for remote areas where no station data is available, they still suffer from shortcomings including poor quality at high temporal and spatial resolution. Combining station measurements with the satellite-based observations can alleviate the problem.

In this study, we applied IRI's Climate Data Tools (CDT) to generate a high resolution (2 arc-minute, ~ 3.3 km) gridded rainfall product by merging CHIRPS rainfall data and 15 CCROM station data. Those datasets were merged for the overlapping period (1980-2010), but limited number of weather station (only 15 across the country) and availability (less than five stations have data available prior to 2000 in Figure 1.2) do not guarantee promising results. The CDT tool was developed based on the methodology by Dinku et al. (2014) and is publically available via https://github.com/rijaf/CDT with a user-guide (file:///C:/CDT/help/html/index.html). The CDT tool provides a set of utility functions for meteorological data quality control, homogenization and merging station data with satellite and others proxies, and all functions are available in the GUI mode via R software.

Before merging CHIRPS and CCROM data, bias adjustment needs to be conducted in order to remove bias in CHIRPS compared to the station data. Then, regression kriging is applied to model rainfall as the sum of deterministic and stochastic components. More details on the merging method can be found in Dinku et al. (2014). In this study, we used a DEM data (2 arc minute) for the final gridding.

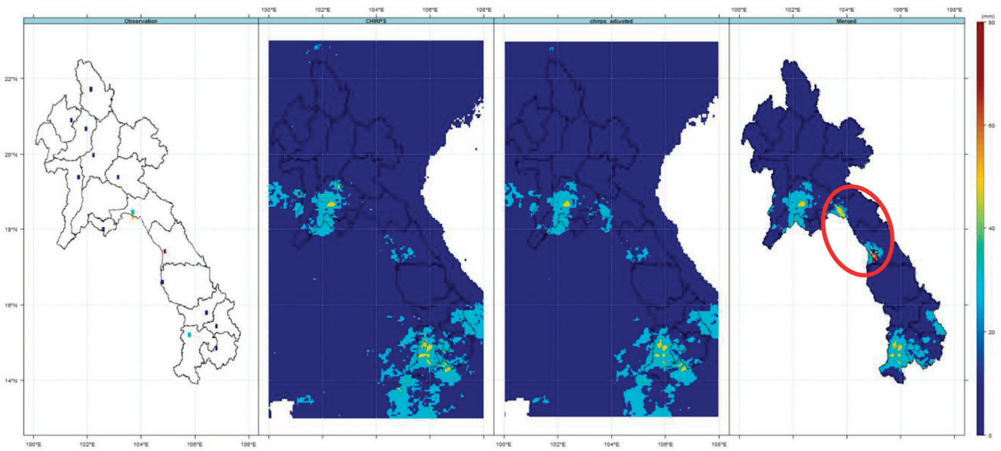


Figure 1.9. Comparison of rainfall products on September 4, 2010: CCROM station (1st column), CHIRPS (2nd column), bias-adjusted CHIRPS (3rd column), and station-CHIRPS combined (4th column).

Figure 1.9 shows an example of the merged rainfall products in comparison with CCROM station data, original CHIRPS and bias-adjusted CHIRPS on September 4^{th}, 2010. The heavy rainfalls in the Borikhamxay and Khamuane province were not captured by CHIRPS on that day, but were reflected to the final merged rainfall product (in red circle). The CDT approach for combining satellite-based global rainfall with local station data looks promising, but more station data is required to ensure further improvement in the final merged products.

1.3.3 Assessing Predictive Skills of Climatic Variables and Vegetation Information for Rice Yield Outlook

In this section, we investigate the relative utility of a variety of information for monitoring rice yield variability, to quantitatively assess their capacity for predicting rice yield at the end of growing season. The information includes: 1) different types of climate information (e.g., rainfall total, frequency and/or dry spells at different growing stages or different time span) and 2) satellite-based data (e.g., MODIS- NDVI, enhanced vegetation index -EVI).

1.3.3.1 Finding relationship between climate variables and crop yields

We explored the relationships between climate variables and rice yields using fifteen years of historical yield data at a provincial level (18 provinces) and rainfall observations from the fifteen CCROM weather stations shown in Figure 1. The analysis was conducted with different climate variables at multiple time scales (one to six months), including: 1) monsoon onset date; 2) monthly rainfall amount (monthly average, mm/day); 3) rainfall amount at different rice growing stages (two to six months during rice growing period); 4) rainfall frequency; and 5) dry spell. In addition, the sensitivities of definition of each climate variable were investigated.

1.3.3.1.1 Correlation between rice yields at different provinces

First, the relationships between provincial rice yields were analyzed. Historical rice yields were de-trended to filter non-climate signals (e.g., technological development) in rice yield variability. Pearson's correlation coefficient and Spearman's rank correlation were used to quantify how climate variables correspond to the detrended observed yields at a provincial level. Figure 7 shows correlations between yields from each province. In terms of rank correlation, yields from each province have a high correlation. However, with respect to the Pearson's correlation, some Northern provinces (Xayabury and Huaphah and Bokeo) have a negative correlation with some central or southern provinces (Borikhamy, Sekong, Champasack and Attapeu). Note that about 84% of the rice-growing area in the wet-season lowlands is located in the central and southern agricultural regions, mainly in provinces lying along the Mekong River Valley (Schiller et al., 2001). Savannakhet (#13), our target area, has in general a strong correlation with yields from other provinces, except a few northern provinces (Phongsaly and Huaphanh).

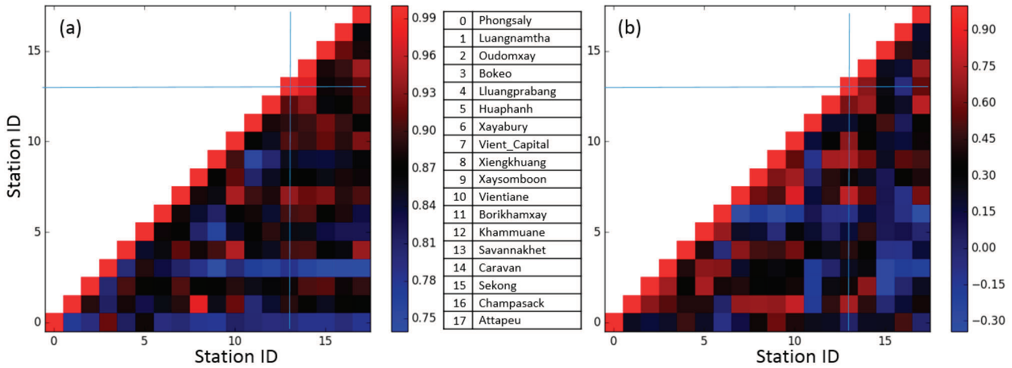


Figure 1.10. Correlation between detrended provincial-level yields: (a) Pearson's R and (b) Spearman's Rank Correlation.

1.3.3.1.2 Correlation between monsoon onset dates and rice yields

Various definitions of Monsoon onset dates can be found in the literature. For instance, local rainfall or convection activity (Ananthakrishnan and Soman 1988; Lau and Yang 1997; Tao 1987), the change of prevailing winds (Holland 1986) or the combined wind-convection criteria (An et al. 1998; Matsumoto 1997; Wang and Wu 1997). In this study, monsoon onset is only defined by rainfall measured at the 15 weather stations across Lao PDR shown in Figure 1.1. Definitions of the monsoon onset dates are based on the literature, but with slight modification (Table 1.1): (1) a long (20 days) running window for total rainfall (Zhang et al. 2002); (2) a short (3-5 day) running window for total rainfall (Higgins et al. 1999); and (3) the first pentad when the mean pentad precipitation exceeds annual mean pentad precipitation in at least three consecutive pentads (Matsumoto 1997).

Onset dates were computed using the "onsetDate" function of IRI's data library (http://iridl.ldeo.columbia.edu/dochelp/Documentation/details/index.html?func=onsetDate&Set-Language=en). For example, the following Ingrid command means "Find the onset date from the CCROM daily rainfall variable for each year from April 20, and within the next 90 days, as the first wet day (greater than 5 mm) within the first 20-day running window that totals 50 mm or more of precipitation and with at least 10 wet days and that is not followed by one 7-day dry spell within the 21 days following the finding of an onset date".

```
SOURCES .CCROM .Lao .stations .Rainfall
  T (20 April) 90 5 20 50 10 7 21 onsetDate
```

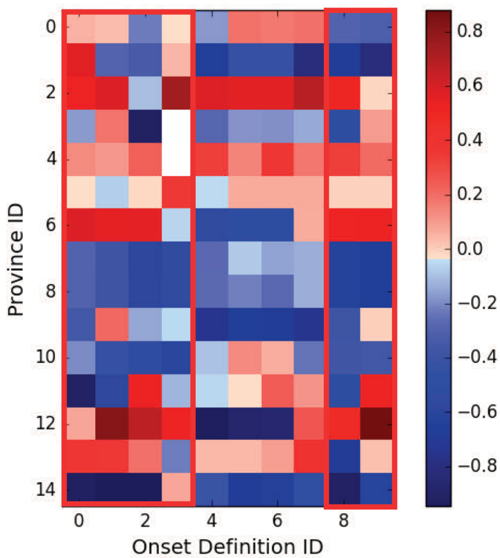
Table 1.1 illustrates each different onset date definition we used in this study and Figure 5 shows the summary correlation coefficients between monsoon onset dates and rice yields for each onset date definition. Note that anomalies of monsoon onset dates (i.e. a positive anomaly means delayed onset) and detrended rice yields were used for computing Spearman's rank correlation.

Table 1.1. Definitions of Monsoon Onset Date

ID	Source	Onset function setup
0	Zhang et al. (2002) with wet days (0 mm/day)	T (20 April) 90 0 20 50 10 7 21
1	Zhang et al. (2002) with wet days (1 mm/day)	T (20 April) 90 1 20 50 10 7 21
2	Zhang et al. (2002) with wet days (3 mm/day)	T (20 April) 90 3 20 50 10 7 21
3	Zhang et al. (2002) with wet days (5 mm/day)	T (20 April) 90 5 20 50 10 7 21
4	Higgins et al. (1999): 0.5 mm/day, 3days total 10mm	T (20 April) 90 0.5 3 10 1 7 21
5	Higgins et al. (1999): 1 mm/day, 5 days, total 15mm	T (20 April) 90 1 5 15 1 7 21
6	Higgins et al. (1999): 2 mm/day, 5 days, total 15mm	T (20 April) 90 2 5 15 1 7 21
7	0 mm/day, 5 days total 20mm	T (20 April) 90 0 5 20 1 7 21
8	Matsumoto (1997) with wet days (0 mm/day)	T (20 April) 90 0 15 71(*) 8 7 21
9	Matsumoto (1997) with wet days (1 mm/day)	T (20 April) 90 1 15 71(*) 8 7 21

*Note: Threshold, 71, varies with station because it is based on annual mean pentad precipitation of each station.

In Figure 1.11, Borikhamxay (#7,8) (central) has a strong relationship between monsoon onset delay and yield regardless of the definition of onset. Attapeu (#14) (southern) and Luangnamtha (#1) (northern), also have a strong relationship between monsoon onset delay and yield regardless of the definition of onset (except 4th definition and 1st & 4th definitions respectively). Savanakhet (#10) shows a positive correlation with delayed onset when onset date is defined with a long period (i.e., 20 days with Zhang's & Mathumoto's definition), but shows negative correlation with a short period definition (Higgines's definition, #5 & #6). Definition of a "wet" day (greater than 0, 1, 3, and 5mm) affects the correlation between rice yields and monsoon onset dates at many stations using Zhang's and Matsumoto's definitions (#0-3 & #8-9). Luangnamtha (#1) (northern & high elevation) and Khammuane (#9) (central) have stronger relationships with a short running window (i.e., Higgins's). Interestingly, Xiengkhuang (#6) and Sekong (#12) have an opposite correlation when different rainfall windows were selected (i.e., a relatively long running window with Zhang's & Mathumoto's definitions vs. a short running window with Higgins' definitions). In summary: (i) monsoon onset dates in an agricultural context (not using an atmospheric definition) should be carefully defined i.e. definition of a "wet" day and the rainfall window (short (3-5 days) vs. long (15-20 day)) affects the correlation between onset date and rice yield; and (ii) geographical difference (high vs. low elevation area) may require different definition of Monsoon onset date when considering its relationship with rice yield.



ID	province name
0	Phongsaly
1	Luangnamtha
2	Oudomxay
3	Lluangprabang
4	Xayabury
5	Vientiane Capital
6	Xiengkhuang
7	Borikhamxay (Borlikhamsay)
8	Borikhamxay (Paksane)
9	Khammuane
10	Savannakhet
11	Saravane
12	Sekong
13	Champasack
14	Attapeu

Figure 1.11. Correlation between monsoon onset date (anomalies) and rice yields (detrended).

There are several factors at play, which explain low rice production. Annual drought and flooding are problems for rice cultivation throughout the central and southern regions, and are only slightly less serious in the northern region of Lao PDR (Eliste et al. 2012). Regular flooding of the Mekong River affects more than 10% of the area planted to wet-season lowland rice in the central and southern agricultural regions (Schiller et al. 2001). Fukai et al. (1998) demonstrated that late season drought alone can reduce grain yields by 30%. In addition, the permeable nature of the sandy soils in the Mekong River Valley aggravates the problems arising from drought (Schiller et al. 2001). Therefore, it is difficult to identify the impact of monsoon onset (or early season drought) on yield variations exclusively.

1.3.3.1.3 Correlation between monthly rainfall amount and rice yields

The relationship between monthly rainfall amounts and rice yields was explored. Figure 1.12 shows a summary of the correlations (Spearman's rank correlation). In Savannakhet, monthly rainfall amounts in June and August are positively correlated with yields, while negatively correlated in September. There is geographical difference in the correlation analysis. Borikhamxay province has a negative correlation coefficient with yield for any month in the growing season.

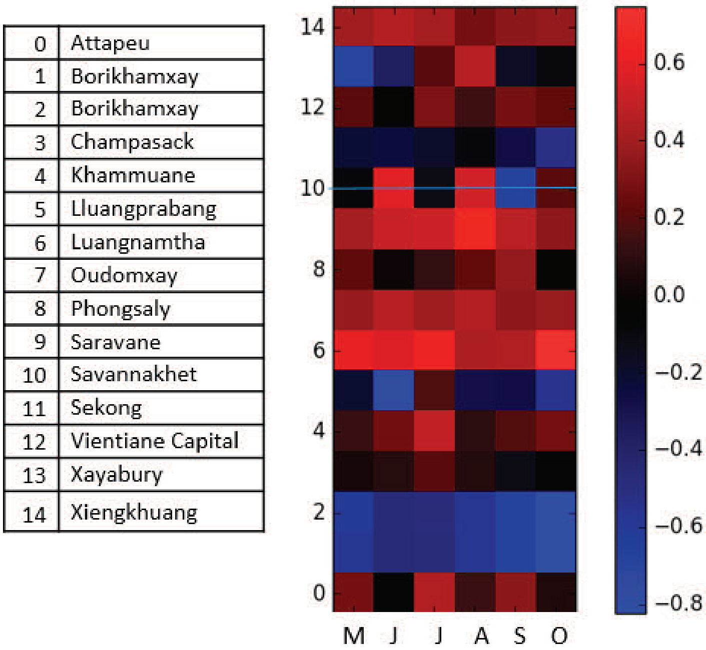


Figure 1.12. Spearman's rank correlation between monthly rain and de-trended yields.

1.3.3.1.4 Correlation between rice yields and rainfall amount at different rice growing stages (two to six months of time span during rice growing period)

Total rainfall amounts within several months (2~6 months) were used to explore their correlation with detrended yields. Table 1.2 shows the summary of the correlation analysis. In Savannakhet, rainfall is positively correlated with rice yields before reproductive and ripening stages (August to October), but negatively correlated in the late growing season. There are geographical differences in the correlation analysis. Some provinces (Borikhamxay, Sekong and Lluangprabang) consistently have negative correlation coefficients. This negative relationship with rainfall amounts seems to be related to flooding. Schiller et al. (2001) reported that 10% of the area planted to wet-season lowland rice in the central and southern agricultural regions is affected by regular flooding of the Mekong River. Luangnamtha and Saravane province show strong positive correlation throughout the rice growing season.

Table 1.2. Correlation between rain for several months and detrended yields

Province Name		Spearman's Rank Correlation												
		MJJASO	MJ	JJ	JA	AS	SO	MJJ	JJA	JAS	ASO	MJJA	JJAS	JASO
0	Attapeu	0.336	0.118	0.273	0.473	0.227	0.282	0.291	0.300	0.400	0.318	0.364	0.336	0.400
1	Borikhamxay	−0.492	−0.483	−0.460	−0.478	−0.697	−0.738	−0.460	−0.469	−0.528	0.747	−0.460	−0.510	−0.615
2	Borikhamxay	−0.492	−0.483	−0.460	−0.478	−0.697	−0.738	−0.460	−0.469	−0.560	−0.747	−0.460	−0.510	−0.615
3	Champasack	0.109	0.073	0.145	0.164	−0.073	−0.055	0.164	0.091	0.200	0.027	0.164	0.136	0.182
4	Khammuane	0.218	0.373	0.482	0.209	0.109	0.227	0.473	0.291	0.264	0.155	0.264	0.255	0.218
5	Lluangprabang	−0.636	−0.655	−0.591	0.073	−0.555	−0.518	−0.291	−0.436	−0.073	−0.773	−0.364	−0.645	−0.355
6	Luangnamtha	0.591	0.600	0.618	0.618	0.464	0.636	0.627	0.636	0.564	0.591	0.582	0.591	0.655
7	Oudomxay	0.355	0.400	0.373	0.345	0.455	0.373	0.373	0.382	0.291	0.418	0.382	0.364	0.291
8	Phongsaly	0.045	0.045	0.000	0.073	0.282	0.018	0.073	0.045	0.218	0.209	0.127	0.055	0.018
9	Saravane	0.609	0.382	0.564	0.609	0.664	0.455	0.564	0.609	0.627	0.664	0.609	0.609	0.609
10	Savannakhet	0.027	0.445	0.318	0.191	−0.245	−0.436	0.309	0.364	−0.282	−0.209	0.345	0.064	−0.336
11	Sekong	−0.291	−0.182	−0.091	−0.118	−0.227	−0.427	−0.200	−0.118	−0.191	−0.327	−0.209	−0.218	−0.227
12	Vientiane Capital	0.144	0.023	0.005	0.144	0.144	0.237	0.070	0.144	0.144	0.144	0.144	0.144	0.284
13	Xayabury	−0.018	−0.782	0.045	0.373	0.255	−0.282	−0.509	0.282	0.518	0.273	0.155	0.264	0.400
14	Xiengkhuang	0.509	0.382	0.409	0.318	0.336	0.382	0.409	0.482	0.391	0.382	0.427	0.491	0.445

1.3.3.1.5 Correlation between rice yields and rainfall frequency

It is often distribution of water rather than lack of total seasonal amounts that is affecting crop growth and final yields. The uneven seasonal distribution of rainfall may expose the crop to a range of mild to severe intra-seasonal dry spells, which may affect the yield adversely. Therefore, in addition to total rainfall amount, we also investigated the relationship between rainfall frequency and detrended rice yields. Two different thresholds (1 vs. 5mm) for the definition of wet days were used.

In Savanakhet, rainfall frequency during the late growing stages (reproductive and ripening stages, in August to October) has a negative relationship with yields, while rainfall frequency in sowing or vegetative stages has a positive correlation (MJ, JJ, MJJ, JJA, MJJA) (Table 1.3). Interestingly, some provinces (Borikhamxay and Sekong) have all negative correlation with yields for any growing period. The same results were found in the relationship with rainfall amount (Table 1.2). Further investigation is required for this province. In general, the threshold (1 vs. 5 mm) used for defining a wet day makes only a slight difference in the correlation results in Table 1.3.

Table 1.3. Correlation between rain frequency and detrended yields.

	Province Name	Spearman's Rank Correlation: Rainfall Frequency vs. Yields (wet day > 1 mm rain)												
		MJJASO	MJ	JJ	JA	AS	SO	MJJ	JJA	JAS	ASO	MJJA	JJAS	JASO
0	Attapeu	0.228	0.269	0.218	0.096	0.091	0.273	0.282	0.105	0.137	0.202	0.227	0.141	0.282
1	Borikhamxay	-0.538	-0.395	-0.419	-0.405	-0.740	-0.881	-0.405	-0.369	-0.562	-0.852	-0.360	-0.489	-0.811
2	Borikhamxay	-0.538	-0.395	-0.419	-0.405	-0.740	-0.881	-0.405	-0.369	-0.562	-0.852	-0.360	-0.489	-0.811
3	Champasack	0.109	0.032	0.032	0.091	-0.173	0.023	0.118	-0.009	0.027	-0.120	0.050	-0.045	-0.045
4	Khammuane	0.401	0.445	0.636	0.096	.0.082	0.598	0.556	0.260	0.169	0.265	0.273	0.309	0.298
5	Lluangprabang	-0.132	-0.342	-0.192	0.069	0.192	0.106	-0.223	-0.384	0.418	0.083	-0.370	-0.215	0.232
6	Luangnamtha	0.733	0.664	0.727	0.779	0.664	0.665	0.711	0.752	0.773	0.715	0.718	0.738	0.745
7	Oudomxay	0.309	0.351	0.464	0.382	0.351	0.424	0.418	0.419	0.275	0.409	0.419	0.282	0.315
8	Phongsaly	0.064	0.105	0.009	0.232	0.327	0.174	0.091	0.091	0.251	0.309	0.091	0.100	0.155
9	Saravane	0.455	0.436	0.465	0.424	0.534	0.564	0.409	0.431	0.596	0.565	0.469	0.478	0.533
10	Savannakhet	0.225	0.333	0.397	0.060	-0.374	-0.205	0.382	0.451	-0.387	-0.005	0.484	-0.155	-0.005
11	Sekong	-0.214	-0.200	-0.055	0.009	-0.173	-0.455	-0.182	-0.036	-0.110	-0.245	-0.068	-0.100	-0.209
12	Vientiane Capital	0.070	0.163	0.014	0.144	0.033	0.000	0.143	0.121	0.091	0.121	0.098	0.033	0.144
13	Xayabury	-0.082	-0.595	0.179	0.478	0.096	-0.312	-0.269	0.383	0.342	-0.023	0.256	0.137	0.173
14	Xiengkhuang	0.405	0.296	0.318	0.427	0.342	0.393	0.388	0.420	0.431	0.519	0.373	0.451	0.473

	Province Name	Spearman's Rank Correlation: Rainfall Frequency vs. Yields (wet day > 5 mm rain)												
		MJJAS	MJ	JJ	JA	AS	SO	MJJ	JJA	JAS	ASO	MJJA	JJAS	JASO
0	Attapeu	0.255	0.174	0.236	0.274	0.219	0.245	0.273	0.237	0.282	0.273	0.255	0.269	0.287
1	Borikhamxay	-0.530	-0.457	-0.406	-0.516	-0.683	-0.802	-0.452	-0.428	-0.574	-0.806	-0.451	-0.483	-0.735
2	Borikhamxay	-0.530	-0.457	-0.406	-0.548	-0.683	-0.802	-0.452	-0.445	-0.574	-0.806	-0.451	-0.489	-0.729
3	Champasack	0.018	0.018	0.082	-0.014	-0.223	-0.041	0.050	0.036	-0.009	-0.064	0.014	-0.009	-0.009
4	Khammuane	0.312	0.411	0.521	0.200	-0.096	0.602	0.498	0.191	0.150	0.233	0.227	0.251	0.264
5	Lluangprabang	-0.351	-0.342	-0.359	-0.124	-0.381	-0.152	-0.156	-0.474	-0.170	-0.443	-0.251	-0.553	-0.229
6	Luangnamtha	0.679	0.588	0.691	0.779	0.591	0.642	0.691	0.725	0.743	0.690	0.688	0.664	0.773
7	Oudomxay	0.300	0.387	0.373	0.355	0.425	0.365	0.382	0.364	0.241	0.392	0.36	0.287	0.287
8	Phongsaly	0.100	0.164	-0.018	0.256	0.387	0.064	0.118	0.082	0.287	0.260	0.101	0.145	0.091
9	Saravane	0.460	0.436	0.497	0.428	0.455	0.560	0.418	0.437	0.518	0.487	0.451	0.519	0.510
10	Savannakhet	0.051	0.455	0.435	0.173	-0.777	-0.352	0.248	0.548	-0.508	-0.435	0.464	-0.182	-0.318
11	Sekong	-0.219	-0.191	-0.046	-0.091	-0.196	-0.333	-0.145	-0.005	-0.209	-0.278	-0.110	-0.164	-0.214
12	Vientiane Capital	0.302	0.116	0.243	0.284	0.144	0.209	0.163	0.267	0.284	0.284	0.277	0.284	0.284
13	Xayabury	0.150	-0.641	0.446	0.428	0.281	-0.287	-0.005	0.391	0.392	0.271	0.182	0.355	0.392
14	Xiengkhuang	0.409	0.374	0.333	0.310	0.288	0.360	0.323	0.373	0.269	0.515	0.264	0.409	0.379

1.3.3.1.6 Correlation between rice yields and dry spells

Dry spell is based only on daily rainfall data using a method described by Stern et al. (1982). For this application, a 'dry' day is defined as a day with < 0.1 mm rainfall and a 'dry spell' as any consecutive number of days defined as 'dry'. For sensitivity test, three different consecutive numbers of days (5, 10 and 15 days) were investigated. Table 1.4 shows Spearman's rank correlation between number of dry spells in a given period (2~6 months) and detrended rice yields. Borikhamxay province shows a negative relationship between number of dry spells and rice yield regardless of growing stage. Some provinces including Luangnamtha, Oudomxay, Saravane and Vientiane (Capital) show a positive correlation regardless of growth stage. In Savannakhet and Attapeu, the number of dry spells in the reproductive and ripening stages (August to October) positively affects rice yields (i.e., positive correlation coefficients in AS, SO, ASO), while there are negative correlations during the vegetative stages (MJ, JJ and JA). Note that the correlation coefficients were not computed when there were an insufficient number of samples; this is indicated by 'nan' in the table.

Table 1.4. Correlation between dry spell and detrended yields.

Province Name		Spearman's Rank Correlation: Number of Dry Spells vs. Yields (dry day < 0.1 mm rain & dry day duration > 5)												
		MJJAS	MJ	JJ	JA	AS	SO	MJJ	JJA	JAS	ASO	MJJA	JJAS	JASO
0	Attapeu	−0.124	−0.056	−0.219	−0.033	0.124	0.253	−0.169	−0.120	−0.065	0.175	−0.142	−0.166	0.000
1	Borikhamxay	−0.603	−0.813	−0.697	−0.697	−0.654	−0.689	−0.813	−0.697	−0.654	−0.561	−0.813	−0.654	−0.561
2	Borikhamxay	−0.603	−0.813	−0.697	−0.697	−0.654	−0.689	−0.813	−0.697	−0.654	−0.561	−0.813	−0.654	−0.561
3	Champasack	−0.330	−0.333	−0.327	−0.257	−0.364	−0.359	−0.333	−0.257	−0.364	−0.340	−0.299	−0.364	−0.339
4	Khammuane	−0.097	0.117	−0.137	0.100	−0.173	−0.221	−0.051	−0.115	−0.217	−0.269	0.075	−0.225	−0.290
5	Lluangprabang	−0.411	−0.270	0.272	0.077	−0.661	−0.433	0.010	0.289	−0.246	−0.401	−0.011	−0.444	−0.335
6	Luangnamtha	0.440	0.536	0.620	0.468	0.405	0.439	0.528	0.555	0.441	0.377	0.550	0.469	0.377
7	Oudomxay	0.699	0.550	0.550	0.667	0.621	0.685	0.572	0.618	0.630	0.676	0.639	0.633	0.639
8	Phongsaly	0.169	0.349	0.359	0.100	−0.032	0.038	0.341	0.269	−0.032	−0.009	0.276	0.087	−0.019
9	Saravane	0.247	0.268	0.410	0.432	0.167	0.161	0.333	0.382	0.261	0.210	0.317	0.349	0.179
10	Savannakhet	−0.019	−0.060	−0.680	−0.434	0.378	0.534	−0.414	−0.688	−0.261	0.177	−0.461	−0.666	−0.141
11	Sekong	−0.287	−0.381	−0.267	−0.287	−0.132	−0.415	−0.306	−0.267	−0.177	−0.283	−0.306	−0.239	−0.189
12	Vientiane Capital	0.225	0.121	0.178	0.248	0.147	0.098	0.121	0.277	0.147	0.121	0.219	0.178	0.121
13	Xayabury	0.064	0.076	0.115	−0.352	−0.145	−0.028	0.150	−0.189	−0.057	−0.141	−0.075	0.023	−0.264
14	Xiengkhuang	0.156	0.392	−0.005	−0.005	0.191	0.261	0.115	0.056	−0.009	0.275	0.163	0.079	0.177

Table 1.4. Correlation between dry spell and detrended yields. (continued)

Province Name		Spearman's Rank Correlation: Number of Dry Spells vs. Yields (dry day < 0.1 mm rain & dry day duration > 10 days)												
		MJJASO	MJ	JJ	JA	AS	SO	MJJ	JJA	JAS	ASO	MJJA	JJAS	JASO
0	Attapeu	−0.060	−0.076	−0.055	0.116	0.116	0.131	−0.076	−0.055	0.116	−0.065	−0.076	−0.055	−0.056
1	Borikhamxay	−0.468	−0.697	−0.697	−0.697	−0.623	−0.458	−0.697	−0.697	−0.623	−0.458	−0.697	−0.623	−0.458
2	Borikhamxay	−0.458	−0.697	−0.697	−0.697	−0.623	−0.458	−0.697	−0.697	−0.623	−0.458	−0.697	−0.623	−0.458
3	Champasack	−0.331	−0.158	−0.158	−0.158	−0.158	−0.280	−0.158	−0.158	−0.158	−0.390	−0.158	−0.158	−0.280
4	Khammuane	0.231	0.301	0.27	0.27	0.301	−0.010	0.301	0.270	0.301	−0.048	0.301	0.301	0.067
5	Lluangprabang	0.126	−0.065	nan	−0.200	0.139	0.178	−0.065	−0.200	−0.027	0.294	−0.346	0.000	0.280
6	Luangnamtha	0.499	0.550	0.550	0.579	0.579	0.601	0.550	0.550	0.579	0.536	0.401	0.550	0.536
7	Oudomxay	0.538	0.505	0.505	0.505	0.382	0.538	0.505	0.505	0.282	0.547	0.61	0.282	0.424
8	Phongsaly	0.121	0.248	0.232	0.232	0.232	0.176	0.248	0.232	0.232	0.221	0.248	0.232	0.121
9	Saravane	0.410	0.327	0.327	0.463	0.463	0.395	0.327	0.327	0.463	0.395	0.327	0.327	0.382
10	Savannakhet	−0.127	−0.298	−0.216	−0.100	0.400	0.014	−0.216	−0.216	0.224	−0.195	−0.216	0.041	0.111
11	Sekong	−0.152	−0.193	−0.471	−0.471	−0.326	−0.319	−0.344	−0.471	−0.471	−0.122	−0.344	−0.411	−0.167
12	Vientiane Capital	0.052	0.147	0.147	0.147	0.147	0.052	0.147	0.147	0.147	0.052	0.147	0.147	0.052
13	Xayabury	0.237	nan	0.000	0.121	−0.100	0.087	−0.100	−0.100	−0.100	0.044	−0.100	−0.100	0.261
14	Xiengkhuang	0.163	0.242	0.242	0.242	0.213	0.242	0.242	0.242	0.213	0.173	0.242	0.213	0.173

Province Name		Spearman's Rank Correlation: Number of Dry Spells vs. Yields (dry day < 0.1 mm rain & dry day duration > 15 days)												
		MJJASO	MJ	JJ	JA	AS	SO	MJJ	JJA	JAS	ASO	MJJA	JJAS	JASO
0	Attapeu	0.124	0.116	0.116	0.116	0.116	0.2S8	0.116	0.116	0.116	−0.020	0.116	0.116	−0.020
1	Borikhamxay	−0.398	−0.697	−0.697	−0.697	−0.697	−0.596	−0.697	−0.697	−0.697	−0.596	−0.697	−0.697	−0.596
2	Borikhamxay	−0.398	−0.697	−0.697	−0.697	−0.697	−0.596	−0.697	−0.697	−0.697	−0.596	−0.697	−0.697	−0.596
3	Champasack	−0.188	−0.158	−0.158	−0.158	−0.158	−0.188	−0.158	−0.158	−0.158	−0.287	−0.158	−0.158	−0.188
4	Khammuane	0.273	0.270	0.270	0.270	0.270	0.005	0.270	0.270	0.270	0.110	0.270	0.270	0.063
5	Lluangprabang	0.482	nan	nan	nan	0.300	0.251	nan	nan	nan	0.359	−0.300	nan	0.324
6	Luangnamtha	0.585	0.579	0.579	0.579	0.579	0.585	0.579	0.579	0.579	0.579	0.579	0.579	0.579
7	Oudomxay	0.583	0.505	0.505	0.505	0.505	0.583	0.505	0.505	0.505	0.583	0.505	0.505	0.471
8	Phongsaly	0.153	0.232	0.232	0.232	0.232	0.193	0.232	0.232	0.232	0.134	0.232	0.232	0.134
9	Saravane	0.452	0.463	0.463	0.463	0.463	0.395	0.463	0.463	0.463	0.395	0.463	0.463	0.382
10	Savannakhet	0.080	−0.300	−0.224	nan	0.400	0.085	−0.224	−0.224	0.400	−0.051	−0.224	0.065	0.280
11	Sekong	−0.153	−0.326	−0.326	−0.326	−0.326	−0.244	−0.326	−0.326	−0.326	−0.197	−0.326	−0.326	−0.133
12	Vientiane Capital	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147	0.147
13	Xayabury	0.359	nan	nan	nan	nan	0.129	nan	nan	nan	0.129	nan	nan	0.258
14	Xiengkhuang	0.124	0.242	0.242	0.242	0.242	0.042	0.242	0.242	0.242	0.042	0.242	0.242	0.042

1.3.3.2 Finding relationship between vegetation information and crop yields

The relationships between vegetation indices and rice yields were investigated at two different scales. First, field observed yield data from NAFRI in 2007 and 2008 (Figure 1.4) were used to find the relationships with a corresponding MODIS 250 m resolution pixel. The field experimental data from NAFRI showed very high variability in management practices (e.g., a wide range of sowing data) as well as yields. For example, in 2007 and 2008, the reported flowering dates range from July 30th (DOY = 211) to November 18th (DOY = 322) and September 1st (DOY =

245) to October 5th (DOY = 279), respectively, as shown in Figure 1.13. We tested many flowering dates ± *n* days, to find a date which produces the highest correlation between NDVI/EVI on that day and harvested yields. Once the date with the highest correlation is found, a linear regression model, $Yield_{pred}$ = slope × NDVI [or EVI] + intercept, was derived for yield prediction. The performance of the prediction model was evaluated using RMSE and coefficient of determination. This analysis was repeated for the year 2007 and 2008 separately in order to see how robust the prediction model is over time. In addition, the analysis was conducted for two different types of cultivars (mid vs. early crop growing cycles), separately.

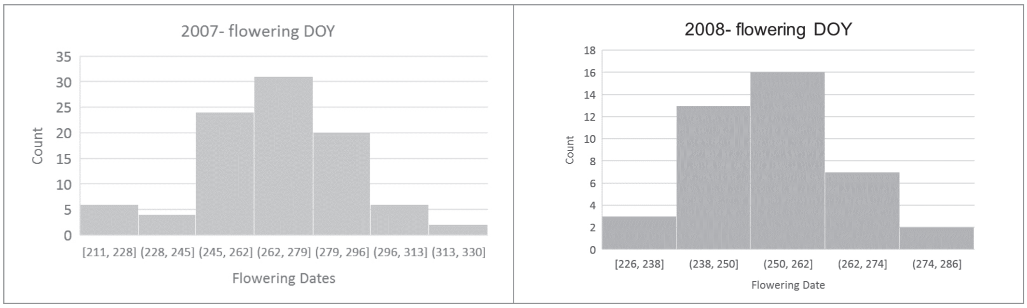


Figure 1.13. Distribution of flowering dates observed in Savannahket in 2007 and 2008.

The results are summarized in Table 1.5. In general, weak correlations between NDVI/EVI and yields (less than 0.5) were found. EVI always showed higher correlation than NDVI. The dates with the highest correlation coefficient are not found to be consistent for different years (e.g., 17 days after flowering in 2007 vs. 17 days before flowering in 2008 with early growing cultivar and NDVI), types of cultivars (e.g., 7 days before flowering with mid-growing and 17 days after flowering with early growing cultivar with NDVI in 2007), and types of vegetation indices (e.g., 7 days before flowering with NDVI and 2 days after flowering with EVI in 2007 with the mid-growing cultivar). Due to the weak correlations between vegetation indices and yields, the performance of the linear prediction model was not accurate, yielding low coefficient of determination and high RMSE. This result can be ascribed to the high heterogeneity in soil, management practices (sowing data, fertilizer application, capacity for irrigation etc.) as well as uncertainty in remotely sensed vegetation information (e.g., impact of cloudiness) and scale mismatch between the 250 m pixel-based NDVI/EVI and small-scale rice farms in Savannakhet. Further investigation is required, particularly on the quality of the NDVI/EVI data as well as identifying factors that affect the correlation or prediction model.

Table 1.5. Correlation between yields and vegetation indices and rice prediction model using Savannakhet field observations in 2007 and 2008.

		All	Crop Growing Cycle (Mid)	Crop Growing Cycle (Early)
NDVI (2007)	Pearson R (p-val)	0.16 (0.14)	0.33 (0.02)	0.16 (0.38)
	Spearman R (p-val)	0.12 (0.25)	0.29 (0.05)	0.13 (0.5)
	Highest Correlation on Flowering Date	+2 days	-7 days	+17 days
	Yield Prediction Model			
	Slope	755.41	1693.96	602.09
	Intercept	1679.25	1116.98	1661.47
	RMSE [kg/ha]	637.3	583.44	643.11
	Coefficient of Determination	0.02	0.11	0.03
	Number of Samples	79	48	31
EVI (2007)	Pearson R (p-val)	0.25 (0.02)	0.36 (0.01)	0.24 (0.2)
	Spearman R (p-val)	0.28 (0.01)	0.39 (0.01)	0.25 (0.18)
	Highest Correlation on Flowering Date	+2 days	+2 days	-2 days
	Yield Prediction Model			
	Slope	1631.38	2346.844	1612.58
	Intercept	1492.52	1239.77	1345.25
	RMSE [kg/ha]	623.92	576.66	633.3
	Coefficient of Determination	0.06	0.13	0.06
	Number of Samples	79	48	31
NDVI (2008)	Pearson R (p-val)	0.28 (0.08)	0.24 (0.17)	0.76 (0.03)
	Spearman R (p-val)	0.29 (0.07)	0.24 (0.18)	0.43 (0.03)
	Highest Correlation on Flowering Date	-7 days	+ 5, +6 days	-17 days
	Yield Prediction Model			
	Slope	919.56	1026.24	3830.16
	Intercept	1388.44	1322.66	-42.76
	RMSE [kg/ha]	817.05	839.36	505.68
	Coefficient of Determination	0.08	0.06	0.57
	Number of Samples	41	33	8
EVI (2008)	Pearson R (p-val)	0.42 (0.01)	0.33 (0.06)	0.78 (0.02)
	Spearman R (p-val)	0.41 (0.01)	0.33 (0.06)	0.5 (0.21)
	Highest Correlation on Flowering Date	0 days	0 days	-14 days
	Yield Prediction Model			
	Slope	2604.93	2236.52	3899.06
	Intercept	940.02	1078.58	611.11
	RMSE [kg/ha]	773.19	815.85	484.98
	Coefficient of Determination	0.17	0.11	0.61
	Number of Samples	41	33	8

Next, we also conducted a similar analysis at a larger scale using province-level annual yield data from the DoA and spatially averaged NDVI/EVI. In this case, NDVI/EVI was aggregated based on a simple arithmetic average only for rice growing areas estimated in 2007-2008, as shown in Figure 1.4. In this analysis, the amount of available data is limited (total 11 samples) because of the limited overlapping periods of MODI NDVI/EVI and annual yield statistics. Therefore, the correlation coefficients have low significance. Since we are using annual yield data, yield anomalies (detrended) were again used for testing the correlation and developing a prediction model, as shown in Table 1.6.

The highest correlation was found on September 30th (DOY = 274) and September 14th (DOY = 257) with NDVI and EVI, respectively. Even though those two dates fall during the peak flowering dates in Savannahket in 2007 and 2008 (Figure 1.13), there is a difference of two weeks between NDVI and EVI. EVI showed a higher correlation with yields and a better performance of the prediction model than NDVI.

Table 1.6. Correlation between yield and vegetation indices and rice prediction model using province-level from 1976-2014

NOVI	Pearson R (p-val)	0.28 (0.4)
	Spearman R (p-val)	-0.05 (0.89)
	Highest Correlation on DOY =	273 (September 30)
	Yield Prediction Model	
	Slope	1.118
	Intercept	-0.712
	RMSE [ton/ha]	0.19
	Coefficient of Determination	0.08
	Number of Samples	11
EVI	Pearson R (p-val)	0.34 (0.31)
	Spearman R (p-val)	0.31 (0.36)
	Highest Correlation on DOY =	257 (September 14)
	Yield Prediction Model	
	Slope	1.225
	Intercept	-0.4868
	RMSE [ton/ha]	0.19
	Coefficient of Determination	0.11
	Number of Samples	11

1.4 CONCLUDING REMARKS

Regarding the predictability of onset date, the results for the Savannakhet region indicate that the regional geopotential height and specific humidity fields in particular, especially when used in conjunction with changes in regional circulation (prevailing wind field) have the potential to be used operationally to improve predictability of total seasonal rainfall as well as the timing of late monsoon onset (post April 25), from the beginning of March. These results also imply similar potential for improved predictability for Lao PDR as a whole, although further research is necessary for other provinces.

The CHIRPS rainfall dataset is a merged product of satellite and station data. It has a higher resolution (5 km) than other satellite-based products, and has thus attracted interest for use in a range of applications. However, our analysis showed that the current CHIRPS dataset relies more heavily on satellite data rather than the station data. Therefore, merging the CHIRPS dataset with CCROM station data is expected to improve the quality of the gridded rainfall products, especially at high resolutions. We used IRI's Climate Data Tools (CDT) to merge CHIRPS and CCROM data and to produce a consistent, higher (2 arc-minute) resolution rainfall dataset, for the long-term period (1980-2010) across the entire country. The merged product showed improvements compared to the original CHIRPS data, but more ground observations are required for further improvements.

As a step-wise approach, we investigated the potential of using climate variables as an indicator of rice yield outlook. First, the relationship between monsoon onset dates and rice yields were explored, using several different definitions of onset date. The results showed that the relationship is sensitive to the definition of onset date, and thus monsoon onset date should be carefully defined specifically for an agricultural context, and not following a typical definition based on atmospheric condition. Geographical characteristics also affect the correlation between onset and rice yields. Next, we examined the relationships between rainfall (amount, frequency and the occurrence of dry spells) at multiple timescales (one to six months) and rice yields. In Savannakhet, rainfall amount and frequency in vegetative stages (MJJ) positively affected the rice yields, while affecting it negatively during the late growing season. Dry spells showed the opposite result: a positive correlation during the reproductive and ripening stages (ASO) and a negative correlation during the vegetative stages. This finding indicates that skillful S2S forecast at different rice growing stages would be able to serve as in indirect indicator of rice yield outlook.

Lastly, we explored the value of monitored vegetation information from satellite data (MODIS 250 m resolution) for crop yield outlook. Our analysis, conducted at both village-level and provincial level yields, showed a weak correlation between NDVI/EVI around flowering stage and rice yields. In general, EVI was more useful than NDVI in predicting yields. Due to the weak correlation, the coefficients of the prediction models were not robust for different time, spatial scale and types of information. Vegetation information around the rice flowering stage still has value for predicting yields at harvest, but prediction models based on simple linear regression should be used with care considering the high uncertainty in the models.

During this first year, we explored the potential of several different forms of available data for S2S forecast, mostly for monsoon onset date prediction and for crop yield outlook. The findings of this study will be reflected in the activities of the second year, during which we ultimately aim to develop an operational agricultural climate risk management system in collaboration with APCC, DMH and NAFRI.

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Chapter 2.

Comparison of Performance of the AquaCrop, EPIC and CERES-Rice Models for Rain-fed Lowland Rice Productivity in Lao PDR

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ABSTRACT

Rice (*Oryza sativa* L.) is a major staple food crop of Laos, accounting for approximately 80% of calorie intake in most rural regions. Among the three rice production systems (irrigated lowland, rain-fed lowland and upland), most rice (about 78% of total rice production) is produced in the wet-season lowland rice ecosystem, implying that the livelihood of the Lao people can be potentially threatened by adverse climatic conditions. In this report, we attempt to calibrate and validate three crop models (AquaCrop, EPIC, and CERES-Rice) for five rice cultivars (TDK1, RD10, RD4, Kodeo, and TSN2) in wet season lowland rice production systems in Laos and to compare those model responses to the rice yields for the five rice cultivars. For this study, we selected the rain-fed lowland rice environment in Savannkhet Province, which is located in the lower central agricultural regions of Laos (15.833 – 17.167 °N, 104.667 – 106.833 °E). Based on their maturities, field locations, and the availability of N-fertilizer application rates, five rice varieties (TDK1, RD10, RD4, Kodeo, and TSN2) were selected and these available datasets were used as inputs for the crop models. Each model was calibrated with the surveyed datasets in 2007 and validated with those in 2008. The fertility stress for the five cultivars was used to calibrate the AquaCrop model; the range of fertility stress in 2007 was between

29 and 48%. The EPIC model was mainly calibrated by adjusting the Biomass-Energy Ratios (WA) to match the observed and simulated rice yields of each variety in 2007. The calibrated WAs ranged from 15 (TSN2) to 75 (RD10). The GenCal program (a built-in program in DSSAT) was used to calibrate the genetic coefficients with the observed flowering dates and rice yields for the five cultivars. The CERES-Rice model accurately simulated the anthesis days and rice grain yields in 2007, with a perfect match between the observed and simulated anthesis days and the MAPE and RMSE values of 3.27% and 0.40 t ha^{-1}, respectively. However, since appreciable nitrogen fertilizer stresses on the rice were simulated, a further study is suggested on experiments of rice growth and development with no stresses including water and nutrients. Based on the performance level and complexity of the three crop models, we concluded that the AquaCrop model can be better to predict attainable yields under no stress conditions, and that the CERES-Rice model can be useful for the determination of the best management practices to achieve targeting rice yields. It is concluded that these process-based crop models can be useful to provide efficacious agricultural managements to enhance food security and to improve the livelihood of the rural people in Laos by the reduction of those adverse impacts of climate variability on rice productivity.

2.1 INTRODUCTION

In Laos, rice (*Oryza sativa* L.) is an important staple crop which accounted for more than 80% of the cultivated areas in Laos, and accounted for approximately 80% of calorie intake in most rural regions (Schiller et al., 2006). There are broadly three rice production systems in Laos: irrigated lowland, rain-fed lowland, and upland. The area of the wet-season lowland rice ecosystem is approximately 575.520 ha and in 2004, 78% of total rice production in Laos was produced in this ecosystem, followed by the dry-season lowland environment (14%) and the upland environment (8%). These values imply that the livelihood of the Lao people can be potentially threatened by adverse climatic conditions. To enhance food security of Laos, it is important to provide efficacious agricultural managements so that those adverse impacts can be reduced on rice productivity.

Modeling approaches have been widely used for the assessment of the impacts the environmental variables including climatic conditions and agricultural managements on rice growth and development. Especially, process-based crop models including AquaCrop, Environmental Policy Integrated Climate (EPIC; Williams, 1990), Crop Estimation through Resources and Environment Synthesis (CERES-Rice; Singh et al., 1994) and the General Large-Area Model for annual crops (GLAM, Challinor et al., 2004) can be useful to determine best management practices such as planting date, cultivar, soil management, and fertilizer application, because these models can simulate how agricultural managements can contribute to crop growth and development and subsequently crop yields (Bannayan et al., 2007). For example, Li et al. (2017) assessed the climate change impacts on rice productivity in the Indochinese peninsula using the GLAM-Rice model which they developed for a rice crop based on the GLAM-Wheat model. A multi-scale approach combining a regional- and field- scale crop models was introduced and applied to the Southeast Asia region for a study on climate change adaptation strategies (Chun et al., 2016).

AquaCrop (Steduto et al., 2009), a simple conceptual model of the Food and Agriculture Organization (FAO) of the United Nations, has provided reliable simulations of crop growth and yield with relatively low input requirement for various purposes. The application of the model is not limited to field-scale practices, such as crop parameterization (e.g., Heng et al., 2009; Mabane et al., 2013) and irrigation scheduling (e.g., Geerts et al., 2010), but has expanded to resource allocations under varying socioeconomic conditions (e.g., García-Vila and Fereres, 2012; Kim and Kaluarachchi, 2016) and large-scale climate change impact assessments on agricultural productivity (e.g., Dale et al., 2017). For example, Mabane et al. (2013) used the AquaCrop model to investigate a relationship between maize (*Zea mays* L.) production and water stress in Pennsylvania (U.S.). They reported that the deviations of the observed and simulated final harvestable maize yields ranged from 2.9 to 15.3%.

The EPIC model has been widely used to simulate the productivity of various crops and locations. Wang et al. (2015) assessed the maize drought hazard risk in Northern China and calculated the maize drought hazard intensity index using the outputs of the EPIC model including water stress and yield. Xiong et al. (2014) presented a simple approach to calibrate the EPIC model for a global assessment of rice productivity with four parameters (potential heat unit: PHU, planting density: PD, harvest index: HI, and biomass-energy ratio: BER). They reported that the simple global calibration method introduced in the study simulated well the spatial pattern of rice yield in the main rice production regions. The EPIC model was used to identify the virtual water content (VWC) of rice and maize in the Korean peninsula (Lim et al., 2017) through an ensemble approach. They showed that the productivity of the major crops (rice and maize) in the Korean peninsula was predicted to increase under climate change larger than that in the past.

A large number of studies have used the CERES-Rice model to investigate climatic and agricultural management impacts on rice productivity in different region. Wang et al. (2017) assessed adaptation strategies (planting date shifting and fertilizer application levels) to climate change for Cambodia. They investigated the climate change impacts on two wet season rice cultivars (Sen Pidao and Phka Rumduol) under RCP4.5 and RCP8.5 scenarios. They found that higher variations in simulated rice yields were predicted at higher fertilizer levels than at lower fertilizer levels. The CERES-Rice model was used for the investigation of the impacts of climate change on rice yields in India (Aggarwal and Mall, 2002). In their study, rice yields were predicted to increase by 6.0-24% in the scenarios run for 2070 with the level of fertilizer application. They also reported that the yield responses to climate change at a low nitrogen fertilizer application rate were smaller than those at optimal fertilizer management. Vilayvong et al. (2015) used the CERES-Rice model to determine management strategies for the two rice cultivars (TDK8 and TDK11) with crop management scenario combinations (eight transplanting dates, two planting densities, and three nitrogen fertilizer levels) between 1980 and 2012 in the model. They reported that the highest average rice yield was predicted when rice was transplanted on 15 Jan with 5 seedlings hill^{-1} and nitrogen fertilizer application rate of 120 kg N ha^{-1} during the simulation period (1980 to 2012). To the best of our knowledge, even though those crop models differ in performance level and complexity, few studies have been conducted on comparing those models for wet season lowland rice production system in Laos.

The objectives of this report are to calibrate and validate the three crop models (AquaCrop, EPIC, and CERES-Rice) for the five rice cultivars (TDK1, RD10, RD4, Kodeo, and TSN2) in wet season lowland rice production systems in Laos and to compare those model performances in the prediction of the rice yields for the five rice cultivars.

2.2 MATERIALS AND METHODS

2.2.1 Study Region

Seasonal cropping cycles for the rice production systems in Laos are presented in Figure 2.1. There are two distinct seasons: the dry season (Nov-Apr) and the wet season (May-Oct). In the lowland rice production ecosystems, rice is generally cultivated in bunded fields under flooding at least part of the season: irrigated lowland with irrigation water and rain-fed lowland with no use of irrigation. In contrast, in the upland production ecosystems, rice is grown in fields with no bund (Schiller et al, 2006). About one month after sowing, seedlings can commonly be transplanted depending on the onset of wet-seasons rains. Harvesting dates are generally between Oct and Nov. However, these dates can vary with the varieties and planting dates. We focused on the rain-fed lowland rice production ecosystems for this study because this ecosystem accounted for approximately 70% of total rice area in Laos, while only 13% of total area is irrigated (Eliste and Santos, 2012).

The rain-fed lowland rice environment in Savannkhet Province in the lower central agricultural regions of Laos (15.833 - 17.167 °N, 104.667 - 106.833 °E) was selected for this study (Figure 2.2). Savarnnakhet is one of the major rice production provinces in Laos with about 40% of the wet-season harvested paddy area and total rice production in the country (Ministry of Planning and Investment, 2010). Lowland rice areas in Savannakhet in 2004 were the largest portion compared with other provinces and accounted for 23% of total lowland rice areas in the country (Inthavong et al., 2012). Rice production in 2014 from the lowland rain-fed rice paddy fields in this Province was approximately 754,300 t (Ministry of Planning and Investment, 2015).

<table>
<tr><td rowspan="2">System</td><td colspan="12">Month</td></tr>
<tr><td>Jan</td><td>Feb</td><td>Mar</td><td>Apr</td><td>May</td><td>Jun</td><td>Jul</td><td>Aug</td><td>Sep</td><td>Oct</td><td>Nov</td><td>Dec</td></tr>
<tr><td>Season</td><td colspan="4">Dry Season</td><td colspan="6">Wet Season</td><td colspan="2">Dry Season</td></tr>
<tr><td>Rain-fed Lowland</td><td></td><td></td><td></td><td></td><td></td><td>Sow</td><td>TP</td><td></td><td></td><td colspan="2">Harvest</td><td></td></tr>
<tr><td>Irrigated Lowland</td><td>TP[a]</td><td></td><td></td><td colspan="2">Harvest</td><td>Sow</td><td>TP</td><td></td><td></td><td colspan="2">Harvest</td><td>Sow</td></tr>
<tr><td rowspan="2">Montane Lowland</td><td rowspan="2">TP</td><td rowspan="2"></td><td rowspan="2"></td><td rowspan="2" colspan="2">Harvest</td><td rowspan="2">Sow</td><td rowspan="2">TP2[b]</td><td rowspan="2"></td><td rowspan="2"></td><td colspan="2">Harvest</td><td rowspan="2"></td></tr>
<tr><td></td><td>Sow[c]</td></tr>
<tr><td>Upland</td><td>Slash</td><td></td><td colspan="2">Burn; make fence and hut</td><td>Plant</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

Figure 2.1. Seasonal cropping calendar for rice production systems in Laos. [a]TP: transplant, [b]TP2: transplant second time (double transplanting), [a]Sow: a dry-season crop is sowed only if irrigation water is available (Adapted from Linquist et al., 2006).

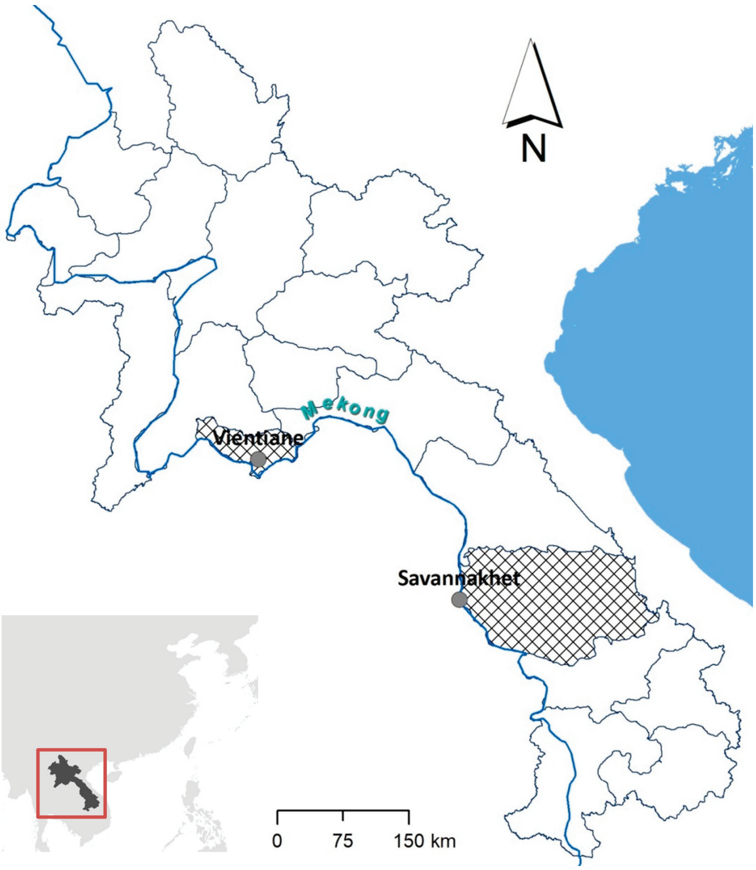

Figure 2.2. Location map of Savannakhet province in Laos.

2.2.2 Data Collection

Table 2.1 summarizes the climatic variables including the mean maximum and minimum temperatures, relative humidity, precipitation, and sunshine duration form 1975 to 2005 at the Savannakhet weather station (Latitude: 16.56°, Longitude: 104.82°). The daily mean temperature (Tmean) varied with the range between 21 and 29 °C and the average Tmean was 26 °C. Especially, the daily mean temperatures during the wet season (May-Oct) were within the optimum ranges of rice growth (Table 2.2). The average daily maximum and minimum temperatures were 31 and 21 °C, respectively.

For rice productivity and potential from rain-fed agricultural systems, rainfall may be the most important climatic variable. However, it should be noted that an increase in seasonal mean temperature can explain approximately 54% in Laos (entire country) of decrease in rice yield (Sanai et al., 2017). Annual rainfall averaged 1445mm in Savannakhet and approximately 90% of the annual precipitation occurred during the wet season. In Savannakhet, the highest precipitation generally occurred in Aug (340mm, approximately 24% of the annual precipitation).

Table 2.1. Maximum, minimum and mean temperatures, relative humidity, precipitation, and sunshine duration from 1975 to 2005 at the Savannakhet weather station (Latitude: 16.56°, Longitude: 104.82°)

Variables	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec	Average
Tmax (°C)	29	31	34	35	34	32	31	31	31	30	29	28	31
Tmin (°C)	15	18	21	24	25	25	24	24	24	21	18	15	21
Tmean (°C)	22	25	28	29	29	28	28	27	27	26	23	21	26
RHmax (%)	94	92	88	88	91	91	92	93	94	92	92	92	92
RHmin (%)	38	40	40	44	53	61	62	66	61	55	48	43	51
RHmean (%)	66	66	64	66	72	76	77	80	78	73	70	67	71
Precipitation (mm)	4	17	32	92	168	256	220	340	219	87	7	2	1445
Sunshine Duration (hr)	239	226	218	198	161	145	128	111	142	211	219	217	1997

Tmean = (Tmax + Tmin) / 2, RHmean = (RHmax + RHmin) / 2

Table 2.2. The response of the rice plant to varying daily mean temperature at different growth stages (adapted from Yoshida, 1981)

Growth Stages	Critical Temperature (°C)		
	Low	High	Optimum
Germination	10	45	20-35
Seedling Establishment	12-13	35	25-30
Rooting	16	35	25-28
Leaf Elongation	7-12	45	31
Tillering	9-16	33	25-31
Primordia Initiation (panicle)	15	-	22-23
Panicle Differentiation	15-20	38	-
Anthesis	22	35	30-33
Ripening	12-18	30	20-25

Sunshine duration is also important for the rice growth and development and can be relatively easy to be converted into solar radiation which is commonly required as one of major inputs for various crop models. Sunshine duration in hour was monitored from the Savannakhet weather station between 1998 and 2011. However, solar radiation was collected from the station between 2000 and 2004 (Table 2.3). For this study, solar radiation data are required to simulate the EPIC and CERES-Rice models. We converted these sunshine duration data into solar radiation using the Anstrom-Prescott equation (Rahimi et al., 2012):

$$\frac{H}{H_0} = a + b\left(\frac{S}{S_0}\right) \qquad [2.1]$$

Where,

a and b = model coefficients (unitless)

H = daily global solar radiation ($MJm^{-2}d^{-1}$)

S = daily sunshine duration (hour)

S_0= maximum possible daily sunshine duration (hour)

The extraterrestrial radiation (H_0) can be calculated from the followings:

$$H_0 = \frac{24}{\pi} G_{SC} d_r [\omega_s \sin(\phi)\sin(\delta) + \cos(\phi)\cos(\delta)\sin(\omega_s)] \qquad [2.2]$$

$$d_r = 1 + 0.0033 \cos(\frac{2\pi}{365} J) \qquad [2.3]$$

$$\delta = \sin(\frac{2\pi}{365} J - 1.39) \qquad [2.4]$$

$$\omega_s = \cos^{-1}[-\tan(\phi)\tan(\delta)] \qquad [2.5]$$

Where,

H_0 = extraterrestrial radiation ($MJm^{-2}d^{-1}$)

G_{SC} = solar constant (4.92 $MJm^{-2}d^{-1}$)

d_r = inverse relative distance Earth-Sun (unitless)

ω_s = sunset hour angle (radian)

ϕ = latitude (radian)

δ = solar declination (radian)

J = Julian date

Table 2.3. The observed sunshine duration hour and solar radiation at the Savannakhet weather station.

Year	Savannakhet (Lat: 16.56˚, Lon: 104.82˚)	
	Sunshine Duration Hour (hr)	Solar Radiation ($MJm^{-2}h^{-1}$)
2000	5.90±3.17	18.77±4.37
2001	6.23±3.10	19.50±4.53
2002	6.49±3.17	19.65±4.50
2003	7.04±3.19	20.54±4.97
2004	6.66±3.28	17.63±4.66

For this study, the model coefficients, a and b were estimated for the entire set, seasonal set (dry season and wet season), and monthly set and the results of each model were compared with the observed solar radiation. The coefficients, a and b of the Anstrom-Prescott equation (eq. [2.1]) can be expressed as the intercept and the slope of the linear regression model of those ratios (H/H_0 and S/S_0), respectively. Therefore, the coefficients, a and b can be obtained by fitting a straight line to H/H_0 and S/S_0. For this fitting, the R software package (R Development Core Team, 2008) was used to determine those coefficients. The performance of the Anstrom-Prescott model was assessed with a few of goodness-of-fit measures including Percent Bias (PBIAS, eq. [2.6]), Mean Absolute Percentage Error (MAPE, eq. [2.7]), R^2 (coefficient of determination), and Root Mean Square Error (RMSE, eq. [2.8]).

$$\mathrm{PBIAS} = \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n} O_i} \times 100 \qquad [2.6]$$

$$\mathrm{MAPE} = \frac{100}{N} \sum_{(i=1)}^{n} \left| \frac{O_i - P_i}{O_i} \right| \qquad [2.7]$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{N}} \qquad [2.8]$$

Where,

O_i = observed value

P_i = predicted value.

For those model simulations, soil properties and characteristics (Table 2.4) and varieties, locations, fertilizer application rates, and rice growth and development (Table 2.5) were collected. The soil samples were collected up to 120cm from the soil surface. The soil texture of top soil (up to 15 cm) at Tasano village was mainly classified as the sandy soil (sand fraction: 92.9%). For this study, we used rice varieties, locations, nitrogen fertilizer application rates, transplanting, flowering and harvesting dates, and rice yields surveyed by Inthavong et al. (2011a). They surveyed those data from 53 and 48 farmers' fields in Savannakhet province in 2007 and 2008, respectively. We selected a total of five rice varieties: TDK1, RD10, RD4, Kodeo, and TSN2 based on their maturities, field locations, and the availability of nitrogen fertilizer application rates. These datasets were used for inputs of the crop models for this study.

Table 2.4. Soil properties and characteristics in Tasano village, Savannakhet.

Depth (cm)	BD (g cm^{-3})	OM (%)	Sand (%)	Silt (%)	Clay (%)	Soil Texture	Wilting Point (%)	Field Capacity (%)
0–15	0.98	0.35	92.90	2.97	4.13	Sand	2.0	5.7
15–30	1.04	0.27	93.99	2.85	3.17	Sand	1.3	4.9
30–60	1.01	0.20	94.67	2.57	2.77	Sand	0.9	4.5
60–90	N/A	0.16	81.49	3.62	14.89	Sandy loam	8.7	13.9
90–120	N/A	0.08	75.88	11.96	12.16	Sandy loam	7.0	13.4

Table 2.5. Collected rice varieties, locations, nitrogen fertilizer application rates, transplanting, flowering and harvesting dates, and rice yields.

Variety	Maturity	Lat (°)	Lon (°)	N fertilizer Application Rate (kg ha^{-1})	Transplanting Date	Flowering Date	Harvesting Date	Observed Yield (t ha^{-1})
TDK1	Mid	17.068	104.881	50	2007/7/10	2007/9/27	2007/10/25	3.5
RD10	Mid	16.956	105.821	N/A	2007/8/16	2007/10/25	2007/11/25	2.8
RD4	Early	16.321	105.974	100	2007/6/30	2007/9/10	2007/9/25	2.8
Kodeo	Mid	16.406	105.660	200	2007/7/15	2007/10/27	2007/11/27	3.5
TSN2	Mid	16.377	105.430	N/A	2007/6/3	2007/9/25	2007/10/20	3.2
TDK1	Mid	17.068	104.881	115	2008/7/30	2008/9/27	2008/10/28	4.9
RD10	Mid	16.956	105.821	32	2008/7/1	2008/9/9	2008/10/22	2.0
RD4	Early	16.321	105.974	10	2008/6/25	2008/9/10	2008/11/17	2.3
Kodeo	Mid	16.406	105.660	0	2008/6/5	2008/9/17	2008/11/19	1.8
TSN2	Mid	16.377	105.430	15	2008/6/3	2008/9/25	2008/10/28	2.1

2.2.3 Crop Models

2.2.3.1 AquaCrop

The AquaCrop model is a multi-crop water productivity model that simulates crop yield response to water, salinity, and fertility stresses. The conceptual structure of AquaCrop is illustrated in Figure 2.3, and Table 2.6 summarizes inputs and outputs of the AquaCrop model. The AquaCrop model simulates daily water balances in the root zone together with green canopy cover (CC) and biomass development on the ground. While the old crop yield function of the FAO (Doorenbos and Kassam, 1979) estimates crop yield using the ratio of actual evapotranspiration (ET) to potential ET, AquaCrop distinguishes between soil evaporation and crop transpiration to avoid confounding effects of non-productive water use on biomass estimation. For water balance simulations in the atmosphere-plant-soil continuum, AquaCrop requires daily climatic inputs (precipitation, maximum and minimum temperatures, and reference ET), soil physical properties (soil moisture contents and saturated hydraulic conductivity), crop phenological parameters, and management information (e.g., irrigation schedules, fertilization, etc.). The model has provided reliable yield estimates under its simple structure and low input requirements (e.g., Hsiao et al., 2009; Heng et al., 2009; Araya et al., 2010; Andarzian et al., 2011; Lin et al., 2012). Fifteen crops including paddy rice have been successfully calibrated and included in the latest AquaCrop ver. 6.0 (available at http://www.fao.org/aquacrop/software/en/) as built-in crops.

We briefly summarize the core structure of the AquaCrop model here, and more details can be found in Raes et al. (2017). The AquaCrop model calculates daily transpiration by multiplying the reference ET, the basal crop coefficient, and the stress coefficient. The stress coefficient ranges between 0 (full stress) to 1 (no stress) to consider effects of water, salinity, and fertility stresses on the transpiration process. Aboveground biomass is estimated using the sum of daily transpiration and the normalized water productivity. The crop yield is estimated simply by multiplying the aboveground biomass and the harvest index:

$$\mathrm{Tr}_i = \mathrm{Ks}_i \times \mathrm{Kc}_{Tri} \times ET_{oi} \qquad [2.9]$$

$$\mathrm{B} = \mathrm{Ks}_{bi} \times \mathrm{WP}^{*} \times \Sigma_{i=1}^{n}\left(\frac{Tr_i}{ET_{oi}}\right) \qquad [2.10]$$

$$\mathrm{Y} = \mathrm{HI} \times \mathrm{B} \qquad [2.11]$$

Where,

Tr_i = transpiration on day i (mm d^{-1})

Ks_i = stress coefficient (unitless)

Kc_{Tri} = basal crop coefficient (unitless)

B = aboveground biomass produced by transpiration (t ha^{-1})

Ks_{bi} = temperature stress coefficient limiting biomass production (unitless)

n = total number of days during a growing period

WP^* = normalized water productivity (t ha^{-1})

ET_{oi} = reference ET (mm d^{-1})

HI = harvest index (unitless)

Y = crop yield (t ha^{-1})

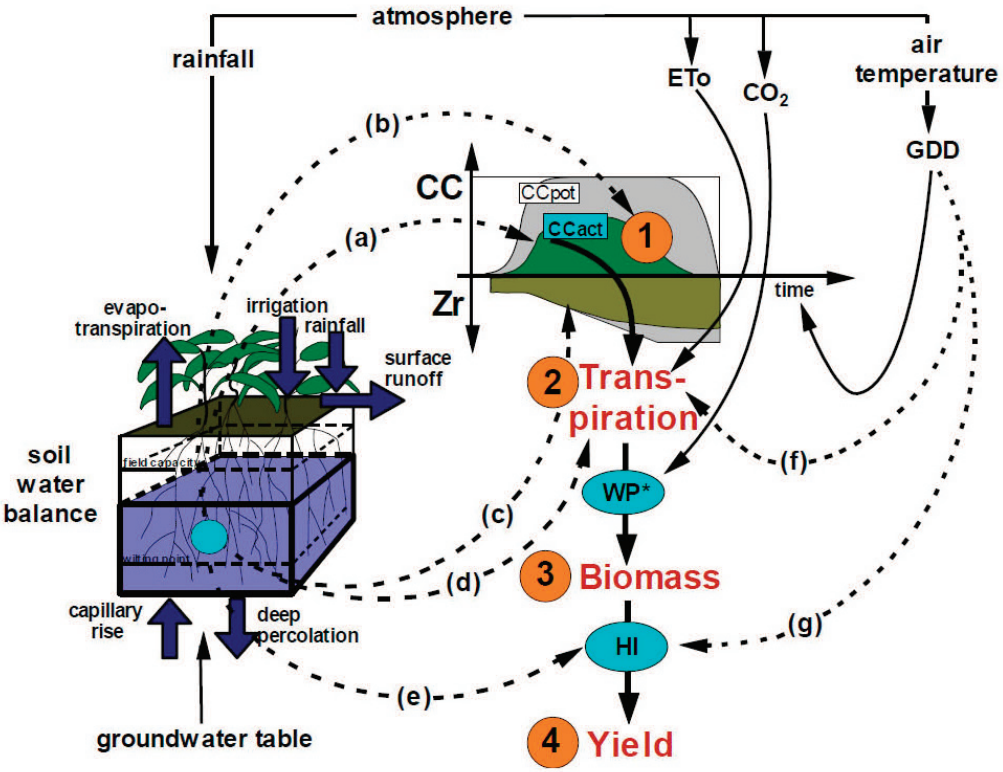

Figure 2.3. The conceptual structure of the FAO AquaCrop model (adapted from Raes et al., 2017).

Table 2.6. Inputs and outputs of the AquaCrop model.

<table>
<tr><th colspan="2">Inputs</th><th colspan="2">Outputs</th></tr>
<tr><td>Climate</td><td>Precipitation
Maximum and minimum temperatures
Reference ET
CO_2 concentration</td><td>Climate and Water Balance</td><td>Transpiration
Soil water content profile
Soil salinity</td></tr>
<tr><td>Soil</td><td>Soil depths
Water contents at permanent wilting point, field capacity, and saturation
Saturated hydraulic conductivity</td><td rowspan="2">Crop Development and Production</td><td rowspan="2">Green canopy cover
Aboveground biomass
Stress information (water, salinity, and temperature stresses)
Harvest index
Crop yield</td></tr>
<tr><td>Management</td><td>Irrigation timing, depths, and salinity
Information for fertility, mulches and weed management</td></tr>
</table>

2.2.3.2 EPIC

The Environmental Policy Integrated Climate (EPIC) model is a process-based model to simulate a field, farm or small watershed considered as a homogeneous unit to climate, soil, landuse, and topography (defined as Hydrologic Landuse Unit, HLU). The EPIC model consist of nine components including weather, hydrology, erosion, nutrient, soil temperature, plant growth, plant environment control, tillage, and economic budgets (Williams, 1990). The EPIC model runs with a daily time step and can perform long-term simulations (up to thousands of years) with the generic crop growth algorithm. The model can simulate crop rotations and other vegetative systems, management practices including fertilization and irrigation. In the model, potential evapotranspiration (PET) can be simulated with five options (Penman-Monteith, Penman, Priestly-Taylor, Hargreaves, and Baier-Robertson). Figure 2.4 illustrates the flow diagram of the EPIC model and the run-specific data files for the simulation of the EPIC model are presented in Table 2.7. More detailed information on the EPIC model can be found in Williams et al. (1984), Williams (1990), Sharply and Williams (1990) and Williams (1995).

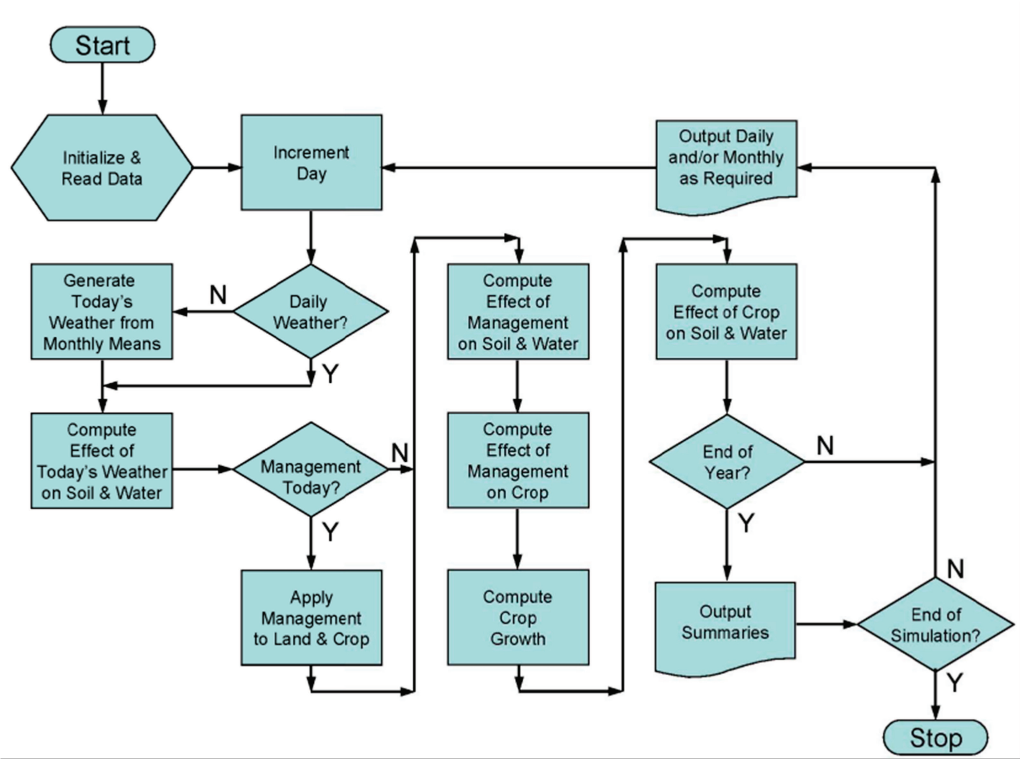

Figure 2.4. Flow diagram of the EPIC model (adapted from EPIC Development Team, 2015)

Table 2.7. List of the run-specific data files for the EPIC model.

Filename	Description
SITE.DAT	A list of site files that can be selected to create runs. The input data for each of the site files is contained in the filename.sit files.
WPM1.DAT	A list of monthly weather stations, ordered by weather station number which can be used in creating runs. This file also gives the latitude, longitude, state and location of the weather station.
Wth5.DAT	EPIC alternate catalog of monthly weather stations for use with the southern oscillation coefficients in WIDX0810.dat
WIND.DAT	A list of wind stations, ordered by wind weather station number, which can be used in creating runs. This file also gives the latitude, longitude, state and location of the wind station.
WIDX.DAT	EPICfile containing coefficients for adjusting monthly averages according to the phase of the southern oscillation, if this correction is requested.
CROP.DAT	Crop parameter file. This file is a list of crops and the associated crop parameters needed by APEX to simulate crop growth.

Table 2.7. List of the run-specific data files for the EPIC model. (continued)

Filename	Description
TILL.DAT	A list of field operations (equipment) and the associated tillage input data.
PEST.DAT	A list of pesticides and the associated input data.
FERT.DAT	A list of fertilizers and the associated input data.
SOIL.DAT	A list of soil files that can be selected to create runs. The input data for each of the soil files is contained in the *filename.sol* files.
OPSC.DAT	List of available operation schedules which can be used to create runs. The input data for each of the operation files is contained in the *filename.ops* files.
TR55.DAT	Data for TR55 runoff estimation
PARM.DAT	Equation parameters and coefficients
MLRN.DAT	Provides for multiple runs at the same site by including an option for selecting consecutive weather seeds and water erosion without reloading the inputs.
PRNT.DAT	Includes the control data for printing select output variables in the sections of the APEX0806.out file and other summary files.
CMOD.DAT	A list of point source files.
WDLST.DAT	A list of daily weather stations and their corresponding latitude and longitude values ordered by weather station number which can be used in creating runs.

2.2.3.3 CERES-Rice

The CERES-Rice model included in the Decision Support System for Agrotechnology Transfer-Cropping System Model (DSSAT-CSM) is a field-scale and process-based model and was used to simulate rice growth and development (Singh et al., 1994) for this study (Figure 2.5). The CERES-Rice model can simulate phenological development, growth of leaves, stems and roots, biomass accumulation and partitioning, soil water balance and water use, and soil nitrogen transformations and uptake by the crop using a daily time step. For the simulation of the CERES-Rice model, major input and output files are summarized in Table 2.8 and Table 2.9, respectively. The minimum weather datasets to run the CERES-Rice model includes latitude and longitude of the weather station, daily values of incoming solar radiation ($MJm^{-2}d^{-1}$), maximum and minimum daily air temperature (°C), and daily total rainfall (mm). More detailed information on the DSSAT CERES-Rice model can be found in Jones et al. (2003).

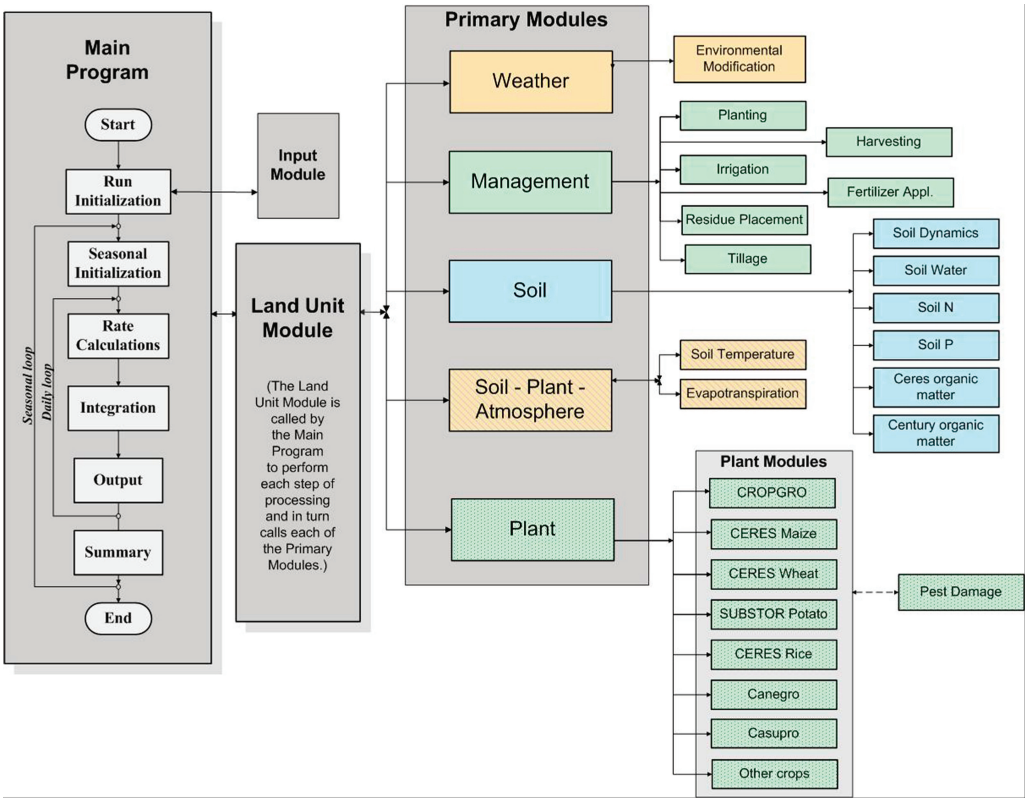

Figure 2.5. Overview of the DSSAT-CSM modular structure (adapted from Hoogenboom et al., 2010).

Table 2.8. Major input files for the CERES-Rice model (adapted from Hoogenboom et al., 2010).

Internal Filename	Example Filenames	External Description
FILEX	*.RIX	Experiment details file for a specific experiment (e.g., soybean at UFGA): Contains data on treatments, field conditions, crop management and simulation controls
FILEW	*.WTH	Weather data, daily, for a specific (e.g.,UFGA) station and time period (e.g., for one year)
FILES	*.SOL	Soil profile data for a group of experimental sites in general (e.g.,SOIL.SOL) or for a specific institute (e.g., UF.SOL)
FILEC	*.CUL	Cultivar/variety coefficients for a particular crop species and model
FILEA	*.RIA	Average values of performance data for a soybean experiment (Used for comparison with summary model results.)

Table 2.9. Major output files for the CERES-Rice model (adapted from Hoogenboom et al., 2010).

Internal Filename	Example Filenames	External Description
OUTO	OVERVIEW.OUT	Overview of inputs and major crop and soil variables.
OUTS	SUMMARY.OUT	Summary information: crop and soil input and output variables; one line for each crop cycle or model run.
SEVAL	Evaluate.OUT	Evaluation output file (simulated vs. measured)
OUTG	PlantGro.OUT	Daily plant growth
OUTPN	PlantN.OUT	Daily plant nitrogen
OUTD	Pest.OUT	Daily pest and disease damage
OUTSC	SoilC.OUT	Daily soil carbon
OUTSN	SoilNi.OUT	Daily inorganic soil nitrogen
OUTWAT	SoilWat.OUT	Daily soil water
OUTT	SoilTemp.OUT	Daily soil temperature
FLDN	FloodN.OUT	Daily flooded field nitrogen processes
OUTLFLD	FloodW.OUT	Daily flooded field management
OUTWTH	Weather.OUT	Daily weather
OUTSPAM	ET.OUT	Daily soil-plant-atmosphere
ERRORO	ERROR.OUT	Error messages
OUTINFO	INFO.OUT	Information output file
OUTWARN	WARNING.OUT	Warning messages

2.2.4 Calibration and Validation of the Crop Models

The surveyed datasets in 2007 were used for the calibration of the three crop models, while those in 2008 were used for the validation of those models (Table 2.5). Three goodness-of-fit measures including PBIAS, MAPE, and RMSE were used to assess the performance of the three crop models in this study. The calibration and validation processes for the three crop models were described below.

In AquaCrop, paddy rice is included as a built-in crop. Since most parameters of the built-in rice are conservative, we used the given phenological parameters for crop simulations. Details about the parameters are found in Raes et al. (2017). The only adjustment applied to the parameters of the built-in rice was to shorten the development length for RD4 (early mature variety). While fertility and water stresses affect crop productivity in the study area (Inthavong et al., 2014), the built-in paddy rice was calibrated for water stress only. Thus, we used the semi-quantitative calibration scheme in the AquaCrop model to consider fertility stress. The model provides an automatic calibration option to determine parameters for crop response to fertility stress. For a strict calibration, two controlled experimental plots are required. One is a plot with fertility stress only, and the other should be well-controlled not to be stressed by water and fertility deficiency. The parameters for fertility stress are automatically determined by biomass reduction percentage and corresponding maximum CC observed in the two plots.

However, because such detailed experimental data were not available, we used simulated yield using the built-in rice for TDK1 in 2007 with given climatic and soil inputs under no consideration of fertility stress. The ratio of the simulated crop yield to the observed yield was used as the biomass percentage reduced by fertility stress alone. The corresponding maximum canopy cover was gained from the MODIS-NDVI images (250 m grid resolution) at the location of TDK1 cultivation by converting it into CC using the model of Johnson and Trout (2012). For TDK1 in 2007, we estimated that biomass production under fertility stress was 60% (moderate biomass reduction) at a maximum CC of 76% (slightly reduced vegetation). For the other cultivars, we applied the same parameters from TDK1.

The user's manual of the EPIC model (EPIC Development team, 2015) provides guidelines for the model calibration. Based on the manual, users are recommended to check accuracies including soil depths, the heat units form planting to harvest, and the plant population and indices or ratios including plant stress levels, the leaf area index, and the Harvest Index (HI) and the Biomass-Energy Ratios (WA). For example, the higher HI or WA, the more grain yield can be simulated for a given level of biomass. For this study, we set the HI value as 0.45, while the WA value was adjusted so that the observed and simulated rice yields of each variety in 2007 were closest. Inthavong et al. (2014) reported that the mean HI value for Savannakhet province was 0.45. The WA values generally vary with the range of 10 to 100.

For the CERES-Rice model, genotype coefficients were determined by the GenCal program, a built-in program in DSSAT. These genotype coefficients are listed in Table 2.10. For this study, because flowering dates and rice yields were collected, the five genetic coefficients P1, P2O, P2R, G1 and G2 were calibrated. Flowering dates are related to the three genotype coefficients P1, P2O, and P2R, while rice grain yield is related to the two genotype coefficients G1 and G2. We used genotype coefficients of the "IRRI RECENT" variety in the RICER046.CUL file as initial values of the genotype coefficients. For this calibration process, the *.RIA file should be created by entering the observed anthesis day and rice yield in a DSSAT built-in module.

Table 2.10. Genetic coefficients for the CERES-Rice model (adapted from Wang et al., 2017)

Genotype Coefficient	Description
P1	Time period (expressed as growing degree days [GDD] at °C above a base temperature of 9 °C) from emergence to the end of the juvenile phase.
P2O	Critical photoperiod or the longest day length (in hours) at which the development occurs at a maximum rate.
P2R	Photoperiod sensitivity coefficient, extent to which the phase development leading to panicle initiation is delayed (expressed as GDD in °C).
P5	Time period (expressed as GDD in °C) from the beginning of grain filling to physiological maturity with a base temperature of 9 °C
G1	Potential spikelet number coefficient as estimated from the number of spikelets per g of the main culm + spike dry weight at anthesis.
G2	Single grain weight (g) under nonlimiting growing conditions, i.e., nonlimiting light, water, nutrients, and absence of pests and diseases.
G3	Tillering coefficient (scalar value) relative to IR64 cultivar under nonlimiting conditions.
G4	Temperature tolerance coefficient.

2.3 RESULTS AND DISCUSSION

2.3.1 Estimates of Solar Radiation

The estimated coefficients of the Anstrom-Prescott equation are summarized in Table 2.11. The model coefficients a and b for the entire dataset were 0.305 and 0.479, respectively. For the seasonal dataset, these coefficients were similar to those of the entire dataset. The performance of the seasonal model for dry season was lower than that for wet season. While the R^2 value of the wet-season model (0.850) was higher than that of the entire-set model (0.87), the value of the dry-season model (0.626) was lower than that of the entire-set model. The model coefficient a for the monthly set ranged between 0.263 and 0.425, and the model coefficient b varied with the range of 0.291 to 0.553. The R^2 value of the monthly-set model was lowest (0.288) in Mar, and was highest in Sep (0.924). All estimates of the coefficients were statistically significant at the significance level 0.001 (***). The range of the estimates of the model coefficients a and b is similar with that of Rahimi et al. (2012). They estimated solar radiation using the Anstrom-Prescott equation in Mashhad, Iran. They reported that the ranges of the model coefficients a and b were 0.25 to 0.34 and 0.34 to 0.62, respectively.

The four measures of goodness-of-fit for the entire-set, seasonal-set, and monthly-set models (R^2, PBIAS, MAPE, and RMSE) were used to evaluate those model performances and the results are summarized in Table 2.12. The poorest results were consistently found from the monthly-set model, while the best results were mainly found from the seasonal-set model except for MAPE. The MAPE value of the seasonal-set model was approximately 7.1% and was slightly higher than that of the entire-set model (approximately 6.9%). Based on these results, we selected the seasonal-set model for the conversion of the sunshine duration data into solar radiation for the Savannakhet weather station and this model result was used for an input weather variable of the EPIC and CERES-Rice models.

Table 2.11. Estimates of the Anstrom-Prescott equation from the Savannakhet station.

Data		a	b	R^2	P-value	RMSE ($MJm^{-2}d^{-1}$)
Entire set		0.305	0.479	0.807	<0.001 ***	2.225
Season	Dry Season (Nov. to Apr.)	0.329	0.452	0.626	<0.001 ***	2.360
	Wet Season (May to Oct.)	0.301	0.475	0.850	<0.001 ***	2.050
Month	Jan	0.263	0.553	0.815	<0.001 ***	4.686
	Feb	0.325	0.457	0.697	<0.001 ***	4.929
	Mar	0.425	0.291	0.288	<0.001 ***	5.179
	Apr	0.321	0.444	0.599	<0.001 ***	6.118
	May	0.308	0.459	0.825	<0.001 ***	6.296
	Jun	0.310	0.437	0.805	<0.001 ***	6.009
	Jul	0.298	0.499	0.898	<0.001 ***	7.002
	Aug	0.302	0.463	0.832	<0.001 ***	6.397
	Sep	0.297	0.490	0.924	<0.001 ***	6.505
	Oct	0.286	0.500	0.697	<0.001 ***	5.739
	Nov	0.275	0.536	0.791	<0.001 ***	4.775
	Dec	0.320	0.470	0.689	<0.001 ***	4.520

Table 2.12. Goodness-of-fit measures for the Anstrom-Prescott models against observed solar radiation.

Estimates	R^2	PBIAS (%)	MAPE (%)	RMSE ($MJm^{-2}d^{-1}$)
Entire	0.777	-0.119	6.934	2.225
Seasonal	0.780	-0.049	7.060	2.090
Monthly	0.001	0.395	26.958	5.739

2.3.2 Calibration and Validation of the Crop Models

2.3.2.1 AquaCrop

Table 2.13 summarizes the yield estimates gained from AquaCrop simulations for the five cultivars. The attainable yields of the varieties planted in the early rainy season were between 5.4 and 6.1 t ha^{-1} under rain-fed conditions in 2007. The RD10 cultivar, which was transplanted in the late rainy season, was more stressed than the other cultivars due to deficient precipitation. The observed yields were 52-57% of the attainable yields, indicating that fertility stress was significant for all the varieties. Inthavong et al. (2014) estimated a yield reduction range of 0-36% from water stress in the Savannakhet province for the TDK1 cultivar in 2007. In Inthavong et al. (2014), rice yield could reach up to 5.8 t ha^{-1} with high nutrient applications in Savannakhet province, implying that the attainable yields from the AquaCrop model seems to be within a plausible range. For yield estimation under water and fertility stresses together in this study, the fertility management efficiency required for the AquaCrop model was assumed as the ratio of observed yield to attainable yield. The simulated rice yields under water and fertility stresses were within a range of 2.9-3.6 t ha^{-1}. The simulated rice yields seem to well agree with the observed rice yields.

The AquaCrop model showed a consistent performance to estimate rice yields for the same cultivars in 2008 (Table 2.14). The differences between the observed and simulated yields were not greater than 0.3 t ha^{-1}. In 2008, the yield reduction from water stress was in 18-33%, while fertility stress was more significant (21-67% of yield reduction) than in 2007. Temperature stress was unlikely activated in both the years 2007 and 2008. The performance metrics for the crop years of 2007 and 2008 are summarized in Table 2.15.

The built-in rice of the AquaCrop model, which was calibrated in the Philippines, seems to have acceptable applicability in theSavannakhet province. Perhaps, the conservative crop parameters for the paddy may have spatial consistency. In addition, yields and water stresses estimated by the AquaCrop model were similar to those estimated by Inthavong et al. (2011a, 2014). This result can be explained by considering that the modeling approach in Inthavong et al (2011a, 2014) was dependent on FAO's reference ET and crop coefficient (Allen et al., 1998). This dependency can be also found in the AquaCrop model. While the fertility management efficiency was a priori estimates obtained from comparison between the attainable and observed yields, the parameters for fertility stress, which indicate moderate biomass reduction at slightly reduced green canopy cover, were of consistency across the cultivars. However, the fertility stress parameters should be used with caution because they are not from controlled experimental plots but estimates from the crop model and remote sensing images.

Table 2.13. Attainable and actual crop yields, and corresponding stresses for 2007 simulated by the built-in rice of AquaCrop in 2007.

Variety	Attainable Yield (t ha^{-1})	Biomass Reduction by Stresses (%)			Observed Yield (t ha^{-1})	Simulated Yield (t ha^{-1})
		Water	Fertility	Temperature		
TDK1	6.1	13	43	0	3.5	3.6
RD10	3.9	46	29	0	2.8	3.4
RD4	5.4	18	48	0	2.8	2.9
Kodeo	6.3	9	44	0	3.5	3.6
TSN2	6.0	25	46	0	3.2	3.3

Table 2.14. Attainable and actual crop yields, and corresponding stresses in 2008 simulated by AquaCrop.

Variety	Attainable Yield (t ha^{-1})	Biomass Reduction by Stresses (%)			Observed Yield (t ha^{-1})	Simulated Yield (t ha^{-1})
		Water	Fertility	Temperature		
TDK1	6.1	24	21	0	4.9	5.0
RD10	6.4	18	65	0	2.0	2.2
RD4	5.5	18	56	0	2.3	2.4
Kodeo	5.8	29	67	0	1.8	2.0
TSN2	5.8	33	60	0	2.1	2.4

Table 2.15. Goodness-of-fit measures for the AquaCrop model against observed rice yield.

Year	PBIAS (%)	MAPE (%)	RMSE (t ha^{-1})
2007	-6.68	7.08	0.42
2008	-6.79	7.93	0.18

2.3.2.2 EPIC

Based on the recommendation of the EPIC guideline, accuracies of inputs, parameters and indices, and ratios were checked using the available surveyed data from the farmers in Savannakhet province. In addition, the EPIC model complexity was considered for this calibration process. The EPIC model may be considered as less complex model. This model complexity and data availability led us to adjust the WA value to calibrate the model. A “trial and error” method was basically used for this calibration. Even though the default values of the basic parameters such as WA and HI are recommended not to be revised because those values were accurate for crops in the U.S., the EPIC manual recommends that those default values be revised for other countries (EPIC development team, 2015). The results are presented in Table 2.16. The WA value of RD10 was highest as 75 and the lowest WA value (15) was found from TSN2. The four parameters (PHU, PD, HI, and BER) were identified in a simple global calibration method presented by Xiong et al. (2014). It should be noted that “BER” in Xiong et al. (2014) is an identical parameter “WA” in this study.

The goodness-of-fit measures (PBIAS, MAPE, and RMSE) are summarized in Table 2.18. Those values were 5.70%, 6.34% and 0.64 t ha^{-1} for PBIAS, MAPE, and RMSE, respectively. Even though those values were low, indicating that the model simulated rice yields were similar to the observed rice yields, it should be noted that rice plants in 2007 suffered from a large nitrogen deficiency. For example, nitrogen stress days were approximately 40 and 27 days for the Kodeo and TDK1 cultivars, respectively (Table 2.16). The models should be calibrated to achieve the observed biomass or yields under environments of no nutrient, water, or temperature stresses (Boote, 1999). Therefore, a further study is recommended on experiments of those rice cultivars with environments of sufficient nutrient and water and favorable temperature.

The EPIC model was validated with the calibrated parameter in 2008 and the result is presented in Table 2.17. For the TDK1 cultivar, the observed and simulated rice yields were 4.9 and 3.7 t ha^{-1}. The model slightly underestimated the rice yield in 2008 with the nitrogen stress days of 3.8 days. The simulated results showed that the nitrogen stress days for RD4 and Kodeo were 69.6 and 73.6 days, respectively. The simulated rice yields for those cultivars were 2.5 and 2.4 t ha^{-1}, respectively. These values were slightly higher than the observed rice yields (i.e., the model slightly overestimated the rice yields for these two cultivars.). In fact, only a nitrogen fertilizer application rate of 10 kg ha^{-1} was applied for the field where the RD4 cultivar was transplanted. No nitrogen fertilizer was applied for the Kodeo-transplanted field (Table 2.5). These results suggest that to achieve the targeting rice yield for the rain-fed lowland rice production ecosystems, more nitrogen fertilizer should be applied for the fields where the cultivars were transplanted. The targeting rice yield is 4 t ha^{-1} for the rain-fed lowland environments (Newby et al., 2013). A nitrogen fertilizer application rate of 60 kg N ha^{-1} is recommended (Linquist and Sengxua, 2001). There are widely and readily available three fertilizers in Laos: 16-20-0, 15-15-15, and urea (46-0-0). For example, to meet the recommended nitrogen fertilizer application rate, when 15-15-15 fertilizer is applied, the application rate should be 400 kg ha^{-1}.

Table 2.16. Calibrated parameter and stress factors of the EPIC model in 2007.

Variety	WA	Stress (day)			Observed Yield (t ha^{-1})	Simulated Yield (t ha^{-1})
		Water	N	Temperature		
TDK1	60	0.0	26.6	0.4	3.5	3.5
RD10	75	1.9	23.4	0.5	2.8	2.6
RD4	55	0.0	13.1	0.4	2.8	2.2
Kodeo	67	18.5	39.4	0.3	3.5	3.5
TSN2	15	0.0	4.7	0.7	3.2	3.1

Table 2.17. Simulated results of the EPIC model in 2008 (validation year).

Variety	WA	Stress (day)			Observed Yield (t ha^{-1})	Simulated Yield (t ha^{-1})
		Water	N	Temperature		
TDK1	60	0.0	3.8	0.5	4.9	3.7
RD10	75	0.0	43.4	0.3	2.0	2.2
RD4	55	0.0	69.6	0.2	2.3	2.5
Kodeo	67	0.0	73.6	0.2	1.8	2.4
TSN2	15	0.0	23.6	0.5	2.1	2.5

Table 2.18. Goodness-of-fit measures for the EPIC models against observed rice yield.

Year	PBIAS (%)	MAPE (%)	RMSE (t ha^{-1})
2007	5.70	6.34	0.64
2008	−1.16	18.79	1.43

2.3.2.3 CERES-Rice

The five genetic coefficients P1, P2O, P2R, G1 and G2 associated with flowering dates and rice yields were determined by the GenCal program, a built-in program in DSSAT. The calibrated genetic coefficients are summarized in Table 2.19. The P1 values ranged between 448.80 (TDK1) and 751.60 (TSN2) and the P2R values varied with the range between 156.40 (TDK1 and RD4) and 252.81 (TSN2), while the P2O values did not largely change over the five cultivars. The G1 values ranged between 38.00 (RD4 and Kodeo) and 48.45 (RD10). However, the G2 values did not largely change over the five cultivars. Vilayvong et al. (2015) calibrated the TDK8 and TDK11 rice cultivars in Laos. These calibrated parameters were within the range of the five genetic coefficients in this study. As shown in Table 2.20, in 2007 (the calibration year), the CERES-Rice model accurately simulated both anthesis days and rice yields for the five cultivars (e.g., only 0.1 t ha^{-1} higher rice yield for Kodeo). Even though the results for the calibration year (2007) showed that the CERES-Rice model accurately simulated rice yields, it should be noted that the CERES-Rice model presented appreciable nitrogen stresses on both growth and photosynthesis. The stress factor is 1 at the maximum stress conditions and 0 at no stress conditions. These results suggest a further experimental study with no stress conditions.

The observed and simulated the anthesis days and rice grain yields for the five cultivars in 2008 are presented in Table 2.21. The differences between the predicted and observed anthesis days were 21 and 7 days for the RD4 and RD10 cultivars, respectively in 2008. The CERES-Rice model estimated the rice yields for the four cultivars except for the RD4 cultivar in 2008 slightly higher than the observed rice yield. For examples, the simulated rice yields were 5.6 and 2.4 t ha^{-1} for the TDK1 and TSN2 cultivars, respectively. The three measures of goodness-of-fit (PBIAS, MAPE, and RMSE) were used to evaluate the CERES-Rice model and the results are summarized in Table 2.22. These results showed that the performance of the CERES-Rice model for the validation year (2008) was lower than that for the calibration year (2007). Those values were -12.91%, 19.28%, and 1.11 t ha^{-1}, for PBIAS, MAPE, and RMSE, respectively. The MAPE value was close to those of Timsina and Humphreys (2006). They reported that the average difference between simulated and observed rice grain yields using the CERES-Rice model was approximately 23%.

Table 2.19. Calibrated genotype coefficients for the five rice cultivars in 2007.

Variety	P1	P2R	P5	P2O	G1	G2	G3	G4
TDK1	448.80	156.40	350.00	10.00	44.73	0.03	1.00	1.00
RD10	520.90	164.20	350.00	11.11	48.45	0.02	1.00	1.00
RD4	496.10	156.40	350.00	11.11	38.00	0.02	1.00	1.00
Kodeo	665.00	228.30	350.00	10.00	38.00	0.02	1.00	1.00
TSN2	751.60	252.80	350.00	10.00	45.22	0.02	1.00	1.00

Table 2.20. Observed and simulated anthesis days, observed and simulated rice yields, and stress factors of the CERES-Rice model in 2007.

Variety	Water Stress		N Stress		Observed Anthesis Day (DAP)	Simulated Anthesis Day (DAP)	Observed Yield (t ha^{-1})	Simulated Yield (t ha^{-1})
	Growth	Photo	Growth	Photo				
TDK1	0.000	0.001	0.268	0.379	79	79	3.5	3.5
RD10	0.000	0.000	0.273	0.400	70	70	2.8	2.8
RD4	0.000	0.000	0.146	0.238	72	72	2.8	3.2
Kodeo	0.001	0.005	0.241	0.358	104	104	3.5	3.6
TSN2	0.001	0.010	0.344	0.471	114	114	3.2	3.2

Table 2.21. Observed and simulated anthesis days, observed and simulated rice yields, and stress factors of the CERES-Rice model in 2008.

Variety	Water Stress		N Stress		Observed Anthesis Day (DAP)	Simulated Anthesis Day (DAP)	Observed Yield (t ha^{-1})	Simulated Yield (t ha^{-1})
	Growth	Photo	Growth	Photo				
TDK1	0.000	0.000	0.211	0.309	59	79	4.9	5.6
RD10	0.012	0.018	0.366	0.494	70	77	2.0	2.6
RD4	0.055	0.079	0.249	0.379	77	56	2.3	2.0
Kodeo	0.000	0.000	0.294	0.424	104	112	1.8	2.3
TSN2	0.000	0.002	0.312	0.434	114	121	2.1	2.4

Table 2.22. Goodness-of-fit measures for the CERES-Rice models against observed rice yield.

Year	PBIAS (%)	MAPE (%)	RMSE ($t\ ha^{-1}$)
2007	-2.75	3.27	0.40
2008	-12.91	19.28	1.11

2.3.3 Comparison of the Crop Models

For the validation year (2008), the performances of the three models were compared with the goodness-of-fit measures. The PBIAS value for the EPIC model was lowest (-1.16%), indicating somewhat overestimation of the rice yields for the five cultivars, while that for the CERES-Rice model was highest (-12.91%), indicating overestimation of the rice yields (Table 2.18 and Table 2.22). With the RMSE values, the AquaCrop model showed better prediction of the rice grain yields for the five cultivars than the other two crop models (EPIC and CERES-Rice). While the RMSE value for the AquaCrop model was 0.18 $t\ ha^{-1}$, those for the EPIC and CERES-Rice models were 1.43 and 1.11 $t\ ha^{-1}$, respectively. In addition, unlike the EPIC and CERES-Rice models, appreciable water stresses were simulated in the AquaCrop model (Table 2.13 and Table 2.14). Similar results can be seen in Figure 2.6. However, the AquaCrop model is generally able to simulate relatively simple agricultural managements. For example, nitrogen fertilizer application rates and timing is not typically required to simulate the model. The information of these managements can be considered as potential adaptation measures to provide best management practices for rice yields. In contrast, those detailed managements including nitrogen fertilizer application rates and timing can be assessed for the best management practices in the CERESE-Rice model.

As shown in Figure 2.6, except for only one cultivar (TDK1), rice yields were lower than 4 $t\ ha^{-1}$ which is the targeting yield for the rain-fed lowland environments in Laos (Newby et al., 2013). Even though the simulation results showed that lower rice yields mainly resulted from nitrogen deficiency and the recommended application rate of nitrogen fertilizer is 60 kg N ha^{-1} (Linquist and Sengxua, 2001), it might not be easy to determine the optimal nitrogen fertilizer application rate to achieve the targeting rice yield, since the responses of nitrogen fertilizer on rice crops can vary with the fertilizer application amount and timing. The AquaCrop has limitation to the adequate simulation of the responses of nitrogen fertilizer application rate and timing on rice growth and development. Therefore, we concluded that a simple crop model like the AquaCrop model can be useful to predict attainable yields under no stress conditions (i.e., water, fertility, and salinity stresses), and that a more complex crop model like the CERES-Rice model can be useful to assess detailed agricultural management information to determine best management practices for the achievement of the targeting rice yields. As shown in Figure 2.6, an ensemble approach can improve the accuracy of the rice yield prediction. However, it should be noted that the calibration in this study was conducted under stress conditions. Battisti et al. (2017) found that an ensemble of completely calibrated crop models better predicted crop yields than any single model.

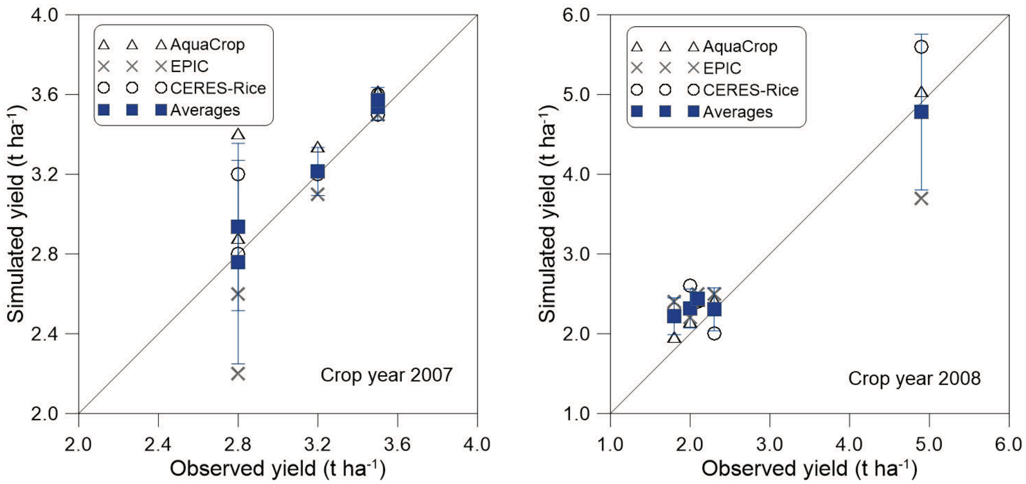

Figure 2.6. Observed and simulated rice yields (a) in 2007(the calibration year) and (b) in 2008 (the validation year). Error bars indicate standard deviations.

2.4 SUMMARY AND CONCLUSIONS

The three crop models (AquaCrop, EPIC, and CERES-Rice) were used to simulate rice yields in wet-season lowland rice production environment in Savannakhet province, Laos and to compare the responses of climatic variables and agricultural managements to rice yields. The five rice cultivar (TDK1, RD10, RD4, Kodeo, and TSN2) considering their maturities, field locations, and the availability of nitrogen fertilizer application rates were selected for this study. The simulation results from those models showed that the AquaCrop and CERES-Rice models slightly overestimated the rice yields for the five cultivars in both the years 2007 and 2008, while the EPIC model slightly underestimated in 2007 and overestimated in 2008. The PBIAS values for the AquaCrop model were -6.68 and -6.79% for the years 2007 and 2008 (Table 2.15), respectively, and those for the CERES-Rice model were -2.75 and -12.91% for the years 2007 and 2008 (Table 2.22), respectively. For the EPIC model, the PBIAS values were 5.70 and -1.16% for the years 2007 and 2008 (Table 2.18), respectively. However, it should be noted that the calibrated parameters and indices were obtained from rice paddy fields under water and nitrogen fertilizer stresses on rice crops. A further study on experiments with no water and nutrient stresses for rice growth and development is suggested to accurately calibrate those process-based crop models. The values of goodness-of-fit measures for those three crop models (Table 2.15, Table 2.18, and Table 2.22) provide evidence that the AquaCrop model better performs than the other two crop models (EPIC and CERES-Rice). Especially, the RMSE values for the AquaCrop model were 0.42 and 0.18 t ha^{-1} in the years 2007 and 2008, respectively, while those values for the EPIC and CERES-Rice models were 1.43 and 1.1 t ha^{-1} in 2008, respectively. These results imply that the AquaCrop model can accurately predict rice yields for the wet-season lowland rice production environment. However, it should be noted that unlike the CERES-Rice model, the AquaCrop model does not require detailed agricultural management information. This information can be considered as best management practices to reduce climate-related risk on rice productivity. It is concluded that the crop models can be useful to provide efficacious climate-related risk on rice productivity. In addition, we concluded that these models can be useful to improve the livelihood of the rural people of Laos and to enhance food security the rain-fed lowland rice production ecosystems in Laos.

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APPENDIX 1.

Letter of Support from NAFRI

NAFRI

National Agriculture and Forestry Research Institute

Nongviengkham, Vientiane, Lao PDR, Tel: +85621770-078, Fax: +85621770-047

Dr. Hong-Sang Jung
Executive Director
APEC Climate Center
12 Centum 7-ro, Haeundae, Busan
Republic of Korea

Dear Dr. Hong-Sang Jung,

Given the fact that agricultural production plays a crucial role in the national economy in Lao PDR, we recognize the importance of adaptation to climate change. This is especially true in rain-fed agriculture, which accounts for a significant portion of the gross domestic production, making the country vulnerable to the impacts of climatic variability and change. In addition, agriculture is highly influenced by natural disaster such as extreme weather events and floods; thus, it is very important to utilize climate information to build agro-climate tools to support rain-fed rice in Lao PDR. In this, it is also important to build collaborative partnerships with advanced institutions to further the agenda of more resilient agriculture in Lao PDR.

We believe that the APEC Climate Center (APCC) has expertise in climate information and agriculture that would be critical in facing these challenges. On behalf of the National Agriculture and Forestry Research Institute (NAFRI), Lao PDR, we wish to state our support for the collaborative project with APCC, Agriculture Risk Management Support for rain-fed lowland rice in Lao PDR (ARMS). Because ARMS aims to support rain-fed rice and increase agricultural resilience with the application of climate information, we believe this is a needed initiative to address the challenges that rain-fed agriculture faces. Throughout the project, NARFI is willing to support and collaborate with APCC, based on our expertise and resources by sharing necessary data, facilitating communication with authorizing government agencies and other stakeholders, including the private sector, as well as by providing support-in-kind and other activities as appropriate to better facilitate the project.

NAFRI and the APCC have been working together from the past and we believe that this project will be successfully conducted, bringing each organization's expertise together. We look forward to the outcomes of this project, which will surely bring benefits to the target area in Savannakhet province and beyond.

Best regards,

Dr. Bounthong Bouahom
Director General
NAFRI

APPENDIX 2.

ARMS Climate Farmer Field Workshop: Training of Trainers and Farmers in Laos

Phonyanang Village Workshop, May 21, 2017

Houmeug Village Workshop, May 25, 2017

2.1 Summary

Related Project: *Agriculture Risk Management Support for rain-fed lowland rice in Lao PDR* (ARMS)

Travel Dates: Tue 16 - Fri 26 May, 2017

APCC Personnel: Dr. Jong Ahn Chun (PI), Dr. Daeha Kim, Ms. Christianne Aikins (PM)

Key Partners: International Research Institute for Climate and Society, National Agriculture and Forestry Research Institute (NAFRI), Provincial Agriculture and Forestry Offices (PAFO), and District Agriculture and Forestry Offices (DAFO)

Purpose: Raise the capacity of government partners to use and communicate climate information, and farmers to understand and apply agro-climate information, and collect information on potential users of the mobile application, in preparation for ARMS project outputs (mobile application and agro-climate advisory), which will be developed during Year 2.

Main Events:

1. ARMS Kickoff Workshop [Wed 17, May 2017]
2. ARMS Climate Farmer Field Workshop: Training of Trainers [Thu 18 - Fri 19, May]
3. ARMS Climate Farmer Field Workshop: Training of Farmers
   a. Phonyanang Village [Sat 20 - Sun 21, May]
   b. Houmeug Village [Wed 24 - Thu 25, May]

Locations:

1. NAFRI Headquarters, Vientiane
2. Agricultural Land Management Section Office, Savannakhet City, Savannakhet Province
3. Savannakhet Province
   a. Phonyanang Village
   b. Houmeug Village

2.2 Background and Purpose

2.2.1 Project Background

Rain-fed rice accounts for a critical percentage of agricultural production in Laos, making the country vulnerable to the impacts of climactic variability and change; a failure in rain-fed rice could have catastrophic ramifications for the economy and national food security. However, this reliance on rain-fed rice also provides an opportunity to build impactful agricultural resilience through a highly specialized project: Agriculture Risk Management Support for rain-fed lowland rice in Lao PDR (ARMS). To reduce climactic risk, ARMS integrates historical weather data and sophisticated climate forecasts with locally-calibrated agricultural models to provided tailored information that provides agro-climate advisory. This approach is complimented by capacity building activities among relevant institutions, such as the Department of Meteorology and Hydrology (DMH) and the National Agriculture and Forestry Research Institute (NAFRI), as well as local farmers, to ensure optimized usage of the output and sustained benefits for the country.

The project will run for two years, and began in March 2017. In particular, ARMS has four objectives:

1. To introduce a risk management framework to enhance preparedness and resilience of agricultural sectors to climatic variability;
2. To develop a mobile application for agro-climate advisory based on S2S climate forecasts;
3. To build capacity of human resources at relevant institutes (DMH and NAFRI) for a sustainable management of the proposed system in this program.
4. To increase farmers' capacity in response to seasonal climate variability through training and educational programs.

These events support the development of the mobile-application based agro-climate advisory, to be developed in the second year of ARMS. Because the outputs of ARMS requires a certain level of capacity of government partners as well as target beneficiaries (farmers), preliminary capacity building through training is absolutely necessary. Additionally, the design and development of this mobile application must be guided by beneficiary need to be both useful and sustainable.

2.2.2 Event Overview

In order to improve the resilience to climate risk in agriculture in Laos, ARMS will develop improved climate data production, facilitate the application of agricultural modelling tools, and finally support the dissemination of agricultural recommendations, like the agro-climate advisory. An essential first step in ensuring that the agricultural recommendations can be produced and received effectively is raising the capacity of those who create these recommendations, and those that receive it. Thus this event was <u>critical in priming the target beneficiaries for outputs</u>, to be delivered in the second year of the project.

How this event supports objectives 3 and 4 may be found below:

Objective 3: To build capacity of human resources at relevant institutes (DMH and NAFRI) for a sustainable management of the proposed system in this program.

- In order to have a successful project, the national and local government must be capable of benefitting from the agro-climate outputs of ARMS and successfully communicating this information to the target beneficiaries: farmers.
- ARMS aims to enable key government partners to translate climate forecasts to agricultural information and evaluate benefits of forecast-based agricultural decision making

Objective 4: To increase farmers' capacity in response to seasonal climate variability through training and educational programs.

- Prepared farmers for the ARMS agro-climate advisory and mobile application, which will be developed in year 2 of the project by enhancing their understanding of the existence and relevance of climate information

ARMS Kickoff Workshop

This was a brief event, taking place in the morning of Wednesday May 17, 2017 at the NAFRI headquarters and is necessary for the launch of ARMS

ARMS Climate Farmer Field Workshop (Training of Trainers and Farmers)

The basic concept behind this workshop is to:

- raise farmers awareness on the impact of climate variability on agriculture production
- train farmers to adapt and mitigate the impact of climate variability and future climate change on crop production through farmer field school

The Training of Trainers supported the ARMS Climate Farmer Field Workshop, so that the local trainers who ran the workshop were trained properly and also so that the provincial government would be more aware of the program and increase their capacity. Learning more about the current agro-climate advisory and the target beneficiaries is critical for making the outputs of ARMS a success, as this information must be tailored to the needs and capacity of these vulnerable groups. APCC played an essential role in training participants on the role

2.3 Schedule & Logistics

2.3.1 General Schedule

Day	Event	Details	Venue	Province
Wed 17 May, 2017	1: Kickoff	*Vientiane* AM: Kickoff Lunch PM: Travel to Savannakhet	NAFRI Headquarters	*Savannakhet*
Thu 18 May, 2017	2: ARMS Climate Farmer Field Workshop Training of Trainers	*Savannakhet* AM: Training of Trainers Lunch PM: Training of Trainers	Meeting room of the Agricultural Land Management Office	*Savannakhet*
Fri 19 May, 2017	2: ARMS Climate Farmer Field Workshop Training of Trainers	*Savannakhet* AM: Training of Trainers Lunch PM: Training of Trainers	Meeting room of the Agricultural Land Management Office	*Savannakhet*
Sat 20 May, 2017	3a: ARMS Climate Farmer Field Workshop Training of Farmers	*Phonyanang* AM: Training of Farmers Lunch PM: Training of Farmers	Phonyanang Village Hall, Outhomphone District	*Savannakhet*
Sun 21 May, 2017	3a: ARMS Climate Farmer Field Workshop Training of Farmers	*Dr. Kim travels back to Vientiane for ASEAN ROK Project)* *Phonyanang* AM: Training of Farmers Lunch PM: Training of Farmers	Phonyanang Village Hall, Outhomphone District	*Savannakhet*
Mon 22 May, 2017	Meeting with NAFRI staff and Field Visit	Discussion of implementation of final event, and visit to water-efficient model vegetable plot	Meeting room of the Agricultural Land Management Office	*Savannakhet*
Tues 23 May, 2017	International Rice Research Institute Climate Farmer Field School Launch	Attended the IRRI Climate Farmer Field School on Rice Seed Varieties as observers	Phailom Village Hall, Champhone District	*Savannakhet*
Wed 24 May, 2017	3b: ARMS Climate Farmer Field Workshop Training of Farmers	*Houmeug* AM: Training of Farmers Lunch PM: Training of Farmers	Houmeug Village Hall, Atsaphangthong District	*Savannakhet*
Thu 25 May, 2017	3b: ARMS Climate Farmer Field Workshop Training of Farmers	*Houmeug* AM: Training of Farmers Lunch PM: Training of Farmers	Houmeug Village Hall, Atsaphangthong District	*Savannakhet*

2.4 May 17: ARMS Kickoff Workshop

2.4.1 Overview

Date: Wednesday, 17 May, 2017
Venue: NAFRI Headquarters
Participants: 25: 3 APCC, 10 NAFRI, 11 other key government officials
Meals: Lunch

2.4.2 Proceedings

As a new project, ARMS held a small kickoff event to signify the launch of the project at the NAFRI headquarters.

2.4.2 Outcomes:

- Official launch of the project
- Increased visibility for ARMS and APCC
- Enhanced relations with key government partners
- Collection of key data from NAFRI headquarters

2.4.4 Agenda

Time	Item	Person
10:00 - 10:30	Arrival and registration	
10:30 - 10:35	Opening announcement	Dr. Thavone Inthavong *NAFRI*
10:35 - 10:40	Welcome Address from the National Agriculture and Forestry Research Institute (NAFRI)	Dr. Vanthong Phengvichit *DDG, NAFRI*
10:40 - 10:50	Introduction of NAFRI's work on climate and agriculture	Dr. Thavone Inthavong *NAFRI*
10:50 - 10:55	Comments and response from the NAFRI executives	Dr. Thavone Inthavong *NAFRI*

Time	Item	Person
10:55 – 11:00	Introduction of APCC	Ms. Christianne Miko Aikins *Project Manager, APCC*
11:00 – 11:20	Introduction of the Agriculture Risk Management Support for rain-fed lowland rice in Lao PDR (ARMS)	Dr. Jong Ahn Chun *Research Fellow, APCC*
11:20 – 11:45	Video presentation by the International Research Institute for Climate and Society of Columbia University (IRI)	Dr. Walter Baegthan, Dr. Eunjin Han *Research Scientists, IRI*
11:45 – 12:00	Question and answer period	
12:00 – 13:45	*Lunch*	

2.5 May 18-19: ARMS Climate Farmer Field Workshop: Training of Trainers

2.5.1 Overview

Date:	Thursday 18 - Friday 19 May, 2017
Venue:	Meeting room of the Agricultural Land Management Office
Participants:	May 18: 25 total, including Dr. Kim, Dr. Chun, and Ms. Aikins May 19: 24 total, including Dr. Chun, and Ms. Aikins
Purpose:	Training of trainers on climate risk management: Enhance ability of partners to translate climate forecasts to agricultural information and evaluate benefits of forecast-based agricultural decision making to enable the successful application of Year 2 ARMS outputs.

2.5.2 Rationale

As explained in section 2.2, this training was a necessary step in enhancing the capacity of provincial and district government to communicate effectively and train local farmers. The key partners here are the Provincial Agriculture and Forestry Office (PAFO) and various District Agriculture and Forestry Offices (DAFO). Key participants in this training went on to assist the ARMS Climate Farmer Field Workshop in the villages the following week. Other participants in this training, who did not assist in the upcoming Climate Farmer Field Workshop, are included to help raise awareness about climate and agriculture, increase their capacity to understand and communicate these concepts, and build support for these and further efforts. PAFO and DAFO officers will be the individuals using and disseminating the mobile phone application, to be developed in 2018. Because of this, raising their capacity as well as investigating their needs, strengths, and weaknesses, is essential for the project.

2.5.3 Outcomes

- Raised local government awareness on the impact of climate variability and climate change on agriculture production
- Enhanced capacity of local government to deliver key trainings on this subject to prepare them for collaboration on the mobile app development and implementation
- Increased visibility of APCC and ARMS
- Gathered information on best practices and challenges encountered in the local setting for communicating climate information effectively

2.5.4 Proceedings

Dr. Thavone Inthavong from NAFRI and Ms. Christianne Aikins from APCC introduced their respective organizations and the training program. Dr. Inthavong explained the importance of this collaboration and welcomed participants.

Dr. Jong Ahn Chun gave a presentation detailing the rational and methodology of ARMS, going into detail about the process-based agricultural models used in the project. Dr. Daeha Kim followed up with a presentation that gave an introduction to the FAO AquaCrop model and its applications. Participants gained an understanding of the science behind ARMS and NAFRI staff requested a training in the AquaCrop model in 2018. This fits well with the intention to build capacity within NAFRI.

Thorough training was given to PAFO and DAFO on how to guide villagers in village mapping, identifying major problems and constraints (focusing on climate change and variability), and prioritizing solutions.

Seven topics were covered on the second day:

- Dr. Thavone introduced the crop calendar introduction
- Miss Ketsana talked about the Farmer Field School
- Ms. Manithaithip Thepphavanh talking about understanding climate variability in agriculture, as well as rainfall distribution, illustrating the

importance of rain gauges to compare to predicted rainfall
- Dr. Khonpany Dounphady discussed soil management, including natural fertilizer
- Mr. Somsamay Vongthilath and Mr. Souliphon Nammoumtry discussed Alternating Wet and Dry (already apply in Soukhuma District, in Champhachak Province) dry direct seeding , and other best management practices
- Dr. Phonevilay Sinavong & Mr. Philavong Khampeth discussed opportunities for generating household income

2.5.5 Agenda

Thursday 18 May 2017		
Time	Topic	Speakers
Session 1	Opening and objectives	
9:00–9:45	• Welcome & need for climate field school • General project overview and introduction to APCC • An overview of climate constraints to productivity for farmers in Savannakhet?	• Dr Thavone Inthavong • Project coordinator, NAFRI • Ms. Christianne Miko Aikins, APCC • DR Tasaka Saphanthong, Dep head of PAFO
9:45–10:00	Coffee break	
Session 2	Farmer needs for climate related information	
10:00–11:00	• Climate Information-based Intervention for Farmers in Savannakhet, Laos • Introduction to FAO AquaCrop model and its applications • Can we provide technical advice to farmers in advance to address these constraints?	• Dr. Jong Ahn Chun, APCC • Dr. Daeha Kim, APCC
11:00–12:00	• Overview of Combined Soil Water Balance Model for characterization of rainfed lowland rice growing environment	• Dr Thavone Inthavong
12:00–1:30	Lunch	
Session 3	Forecasting and modelling tools 1	
1:30–3:15	• Overview of village training methods for Phonyanang and Houmeug Villages	• Mrs Khamphamy Khodyhotha, NAFRI
3:15–3:30	Coffee break	
3:30–5:00	• Hands-on practice in village exercises to map vulnerabilities, list problems, and identify potential solutions	• All

Friday 19 May 2017		
Session 4	Forecasting and modelling tools 2	
9:00–10:00 10:00–10:30	• Introduction a dynamic crop calendar and Agro-climate advisory for rainfed lowland rice planting in 2017 wet season • The basic understanding of weather and climate information	• Dr Thavone Inthavong, NAFRI • Miss Manithaithip, NAFRI
10:30–10:45	Coffee break	
10:45–11:30 11:30–12:00	• Soil nutrient and fertilizer recommendation • Crop establishment techniques (e.g.direct seeding, Best management practices-BMP)	• Mr Khonpany Dunphady- DALMP • Mr Soulapon, PAFO /Mr Somsamay Vortilath, NAFRI
12:00–1:30	Lunch	
Session 5	Delivery to farmers	
1:30–2:45 2:45–3:15	• How do Savannakhet farmers currently receive information about climate and agriculture? • Concept of Climate Field Workshop module	• Mr Bounteo, Head of Agri.& Land Management section, PAFO • Mrs Dalivanh Samonty, NAFRI
3:15–3:30	Coffee break	
3:30–4:15	• Introduction on household income generating concept • General discussion on development of climate workshops for agriculture for Laos	• Dr Phonvilay Sinavong & Mr. Philavong Khampeth, NAFRI • All participants
4:15–5:00	• Climate advisory dissemination to farmers and the upcoming ARMS mobile application based agro-climate advisory • Closing	• Dr. Jong Ahn Chun, Dr. Daeha Kim, APCC • Dr Thavone Inthavong

2.6 May 20-21: ARMS Climate Farmer Field Workshop in Phonyanang

2.6.1 Overview

Date: Saturday 20 - Sunday 21 May, 2017

Venue: Phonyanang Village, Outhoumphone District, Savannakhet Province, Lao PDR

Purpose: Prepared target beneficiaries for Year 2 ARMS Outputs to translate climate forecasts to agricultural information and evaluate benefits of forecast-based agricultural decision making to enable the successful application of Year 2 ARMS outputs

Participants: May 20: 23 total, including Dr. Kim, Dr. Chun, and Ms. Aikins, PAFO, DAFO and village elders
May 21: 53 total, including Dr. Chun, and Ms. Aikins, PAFO, DAFO, village elders, and many villagers

2.6.2 Proceedings

The basic concept behind the ARMS Climate Farmer Field Workshop was to:

- Prepare target beneficiaries for the Year 2 ARMS outputs by
  - raising farmers awareness on the impact of climate variabilities on agriculture production through the identification of local climate-related problems
  - training farmers to adapt and mitigate the impact of climate variability and future climate change on crop production by using agro-climate information
- Increase the visibility of ARMS and APCC
- Gather important information on the needs and capacities of the target beneficiaries to help build the ARMS mobile application, to be developed in Year 2

During the workshop, farmers showed an impressive awareness of the impacts of climate variability on their livelihoods and were eager to access data that may improve their farming practices. In addition, they seemed extremely eager to welcome new ideas, however in the past, some government programs had given seeds to help, then collected the produce during harvest season for "testing" leaving the villagers with nothing. They needed to be reassured that this would not happen during this project.

The Village Head noted that the region has extremely low productivity at 1.5-2.9 tons/hectare (with a national average of 3.5). During discussions, the village elders identified four major problems:

1. Water: Variable rainfall, arriving too early or too late, can be devastating for planting. The villagers prioritize accessing improved rainfall forecasts to avoid these issues
2. Labour shortage: Farming has been left to the elderly as the youth have moved to cities
3. Growing techniques: They plant seeds exclusively obtained from the previous season, noting that this may not be the best variety for the upcoming season. They wish to use appropriate rice varieties for the forecasted season.
4. Market: The price of grain is too low and their market access is minimal, being so isolated

While some issues such as market and labour shortage fall outside the scope of this project, it was heartening to note how eager they were to obtain tools like the dynamic field crop calendar and eventually the mobile phone application. They proposed the following solutions to these problems:

1. Accessing updated crop calendar
2. Build ponds for water storage
3. Obtain a direct seeding machine
4. Obtain rice seeds that are tolerant to disease, drought, or flood
5. Pesticides
6. Plant crops that requires less water
7. Find a low interest fertilizer loan

8. Apply new technology suitable for the area
9. Plant a rice seed that has a high market demand
10. Apply organic fertilizer (which NAFRI demonstrated how to make on the second day)

APCC discussed with the villagers and local staff about what areas were relevant to APCC's work, thus indicating areas for overlap. The villagers now understand what a climate crop calendar is and how to use it, which sets the stage for next year's project in developing a mobile app to disseminate the updated crop calendar monthly.

2.6.3 Outcomes

- Improved farmers' understanding of climate risk management and how they could use climate information in taking appropriate management decisions on crops, soil and water in relation to seasonal climate variability.
- Rural farmers in the village received hands-on training in their fields on appropriate climate risk management practices such as how to measure daily rainfall, rainfall visualize, soil and water management techniques, know how to use seasonal climate advisory and a dynamic cropping calendar.
- Increased visibility of APCC and ARMS
- Gathered information on best practices and challenges encountered in the local setting for communicating this effectively

2.6.4 Agenda

Phonyanang Village		
Date	Program	Responsibility
Saturday 20 May, 2017		
8:00-8:30	Registration	Administration
8:30-8:45	Opening Session	Head of Relevant District Agriculture & Forestry Office
8:45-9:10	General project overview on ARMS and the use of climate information	Dr. Jong Ahn Chun, Dr. Daeha Kim, Ms. Christianne Aikins, APCC
9:10-9:25	ARMS Climate Farmer Field Workshop overview (Climate risk management overview)	Dr Thavone Inthavong, NAFRI-CFS Team
9:25-10:30	Select 5 Key farmers to serve as the core CFS team: • collect data/general information about the condition of the prospective location for the CFS program	NAFRI-CFS Team -Farmers
10:30-10:45	Coffee break	
10:45-12:00	Mapping of Agri. land, vulnerable area (flood & drought), identify climate risk on crop production.	Village CFS committee & all Farmers
	Present the results: • Discuss the results of mapping, understanding climate risks faced by farmers in the village • Identify the problems associated with the climate risks and to formulate recommendations to solve the problems • Revise the mapping of climate risks	All participants
12:00-13:30	Lunch	
13:30-14:30	Agricultural applications of APCC MME seasonal forecasts	Dr. Jong Ahn Chun, APCC
14:30-15:00	Introduction a dynamic crop calendar and Agro-climate advisory for rainfed lowland rice planting in 2017 wet season	Dr Thavone Inthavong NAFRI
15:00-15:15	Coffee break	
15:15-16:00	• Discussion on the basic understanding of weather and climate information • Rainfall formation, changing in min. and max temperature, solar radiation • Understanding of seasonal climate forecast (rainfall below normal-BN; Normal-N; above normal-AN • Traditional climate forecasts/local knowledge (observed from animals or plant) • Practice how to measure climate data: rain gauge • instruction on daily rainfall collection by using simple tools (plastic bottle) • rainfall visualize to draw rainfall visualize	Miss Manithaithip, NAFRI

Sunday 21 May, 2017		
9:00-9:45	Best Management Practice (BMP) to improve crop yield productivity	Dr Thavone Inthavong NAFRI
9:45-10:30	Soil constraints and soil nutrient management based on: • Understand soil physical properties • Soil Doc • Practice how to measure soil pH	Mr Khonpany Dunphady- DALMP
10:30-10:45	Coffee break	
10:45-12:00	• Soil improvements by using leguminous crops, farm manure, compost, biochart…	Mr Khonpany Dunphady- DALMP
12:00-13:00	Lunch	
13:00-14:00	Crop establishment by using dry direct seeding technique	Mr. Souliphon Mammoumtry, Savannakhet agricultural land managment
14:00-15:00	Demonstration: • How to make compost fertilizer and Bio-char • How to use Dry direct seeding tool	Mr Khonpany Dunphady Mr Somsuk Bounphaphone Mr Souliphon Mammoumtry
15:00-15:30	Coffee break	
15:30-16:00	Closing	APCC and DAFO

2.7 May 22: Interview on App Development

2.7.1 Discussion on Future of ARMS and App Development

A discussion was held with NAFRI and PAFO staff on ARMS and the mobile phone app which will be developed in 2018. The staff were eager to use this app to communicate with farmers, saying that they would teach the Representative Farmers (the focal point farmers for each village intervention) how to use the app. They shared the following requests/considerations:

- It must be in Lao and English
- It must be for iOS and Android
- It must include the climate advisory (generally 2 pages) that shares information on how to adapt to the weather forecast, updated 2 times per month
- It should not be too large, as phones generally have small capacity
- Try to improve IT capacity of NAFRI during the development

They noted that the crop calendars are not posted anywhere online, instead are given as a physical poster to villages. This means that the crop calendar is not consistently updated, making an urgent need for the mobile application.

Additionally other features were discussed as potential additions. For example, it could be used as a platform to collect rainfall data for the farmers who use NAFRI rain gauges. They also proposed have a static “encyclopedia” of best practices and techniques, which could include mini-guides on how to prevent pests and disease, soil improvement techniques, etc. They suggested having links to how-to videos as a way to keep the application size down, where volunteer university students could work together with NAFRI/PAFO to develop these videos.

Unrelated to the application, they requested some assistance in teaching more people how to make the crop calendar. Currently Dr. Thavone is the only individual who is familiar with all aspects of its development. PAFO staff have requested NAFRI to be trained in this, and NAFRI agreed, however they also look to APCC to have complimentary activities.

2.8 May 23: International Rice Research Institute Farmer Field School Opening Ceremony

On May 23, 2017, APCC and NAFRI staff attended a Farmer Field School (FFS) supported by the International Rice Research Institute (IRRI), the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), and Cuso International (CUSO). The FFS was focused on the management and use of a range of rice varieties, and would continue weekly for the following 2 months.

Dr. Thavone Inthavong introduced APCC and NAFRI, and gave a presentation in Lao on the dynamic crop calendar and ARMS. Contacts were made with local IRRI staff, who agreed to provide some useful agricultural datasets for ARMS model development and validation.

APCC also was introduced to Mr. Bounlieng Chanvanhpheng, the Deputy Director of PAFO, and shared information on ARMS.

2.9 May 24-25: ARMS Climate Farmer Field Workshop in Houmeug Village

2.9.1 Overview

Date:	Wednesday 24 - Thursday 25, May, 2017
Venue:	Houmeug Village, Atsaphangthong District, Savannakhet Province, Lao PDR
Purpose:	Prepare target beneficiaries for Year 2 ARMS Outputs to translate climate forecasts to agricultural information and evaluate benefits of forecast-based agricultural decision making to enable the successful application of Year 2 ARMS outputs
Participants:	May 24: 47 total, including Dr. Chun, and Ms. Aikins, PAFO, DAFO, village elders, and many villagers May 25: 41 total, including Dr. Chun, and Ms. Aikins, PAFO, DAFO, village elders, and many villagers

2.9.2 Proceedings

The basic concept and content behind this workshop was the same as the Climate Farmer Field Workshop held in Phonyanang Village (Section 6). Houmeug Village, however, had many more problems than Phonyanang, due to the poor soil quality, extremely arid climate, and high incidence of pest and disease. The villagers listed over 25 problems, including soil quality (including issues of salinity), the uncertainties of rainfall and hot weather, insect and pest, low market price, lack of labour, and insufficient area to grow livestock feed.

Similarly, Houmeug Village proposed a host of solutions. They highlighted the desire for improved weather forecasting and the use of specific rice varieties to suit seasonal projections, which will be directly disseminated by or supported through APCC's planned activities for 2018. They too were eager to learn about the ARMS outputs, and indicated that they would use the dynamic crop calendar to inform their planting decisions. Other solutions were mentioned and, while important, they had less relevance to APCC, such as the increased amount of livestock feed production and improving soil conditions.

APCC staff explained ARMS and the relevant work being done across Asia and the Pacific. Dr. Chun shared his expertise on agricultural models and adapting to climate variability.

2.9.3 Outcomes

- Improved farmers' understanding of climate risk management and how they could use climate information in taking appropriate management decisions on crops, soil and water in relation to seasonal climate variability.
- Rural farmers in the village received hands-on training in their fields on appropriate climate risk management practices such as how to measure daily rainfall, rainfall visualize, soil and water management techniques, know how to use seasonal climate advisory and a dynamic cropping calendar.
- Increased visibility of APCC and ARMS
- Gathered information on best practices and challenges encountered in the local setting for communicating this effectively

2.9.4 Agenda

Please see section 3.6.4 for the agenda.

2.10 Photos

2.10.1 Kickoff Workshop

Dr. Vanthong Phengvichit, the Deputy Director General of NAFRI gives the Welcome Address at the Kickoff Workshop (17 May)

Ms. Aikins delivers an introduction on APCC (17 May)

2.10.2 Training of Trainers in Savannakhet

Dr. Chun delivers a presentation on ARMS (18 May)

Dr. Kim delivers an introduction to the FAO AquaCrop model and its applications (18 May)

Group photograph (19 May)

2.10.3 Training of Farmers in Phonyanang Village

Open air venue where village elders gather for the first day of the workshop (20 May)

Dr. Chun assists village elders in mapping climate vulnerabilities of their village (20 May)

Dr. Chun delivers an address on the relevance of ARMS (21 May) to villagers and village elders

NAFRI staff demonstrate variable rainfall distribution and the importance of rain gauges for rainfall monitoring (21 May)

Demonstration of organic natural fertilizer production (21 May)

Group photo (21 May)

2.11 IRRI Farmer Field School

NAFRI Staff Ms. Khamphamy encourages female participants to give questions on the variable crop calendar (22 May)

2.12 Training of Farmers in Houmeug Village

Dr. Chun welcomes participants and gives a presentation on ARMS (24 May)

Demonstration of the method to create organic fertilizer (25 May)

Group photo, with the presenting of new rice seed varieties donated by NAFRI to the Village Head (25 May)

APPENDIX 3.

Stakeholder Engagement and Capacity Building

Building capacity of relevant government institutes in Lao PDR as well as successful integration of climate and agricultural information into decision making will lead to sustainability of the project outcomes and eventually to improve resilience of rice farming to the climate variability and change. At the end of the first year project, IRI conducted training workshops at two major partner institutes, NAFRI and DMH separately.

A training workshop was held at DMH from November 8th to 11th by inviting 10 DMH staffs and 9 local staffs from different provinces (Figure A3.1a). The workshop aimed to improve capacity of DMH staffs for generating more reliable climate information. Particularly, the goal of the workshop was to 1) help DMH use the best data available to determine which variables can give us the most predictability for seasonal rainfall and for subseasonal timescales, such as onset date, and 2) help DMH for effectively communicating climate science, especially when there is uncertainty, can be very challenging. Participants were trained in how to use the Climate Predictability Tool to produce seasonal forecasts for rainfall, using station data that they brought from their respective provinces. They were able to perform experiments to determine what months or combinations of months were able to provide higher predictability using sea-surface temperatures, and to examine the results for predicting different combinations of rainfall seasons. Most participants were able to identify some reasonable amount of predictability and to better understand the processes that produce rainfall and to explain those relationships.

Another training workshop was held at NAFRI from November 8th to 14th, 2017 (Figure A3.1b). Total 19 people participated in the training: 15 NAFRI staffs, 2 people from Provincial Agriculture and Forestry Researchers (PAFO), 1 from Outhomphone District Agriculture and Forestry Researchers (DAFO) and 1 from Atsaphanthong DAFO. The main objective of the NAFRI workshop was to raise awareness of climate related risks and lead to a better understanding of benefits from basic climate risk managements. The workshop covered general topics including "Introduction to climate risk management in agriculture", "Weather and climate variability", "Probabilistic forecasts" and "Climate risk assessment and management". The participants were also exposed to some successful examples of climate advisory and decision supporting tools developed by IRI. This workshop is expected to support communication on activities aimed at enabling decision makers to understand the information, communicate successfully and act on it effectively.

(a)

(b)

Figure A3.1. Training workshops at (a) DMH and (b) NAFRI

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Research Report 2017-13

Agriculture Risk Management Support (ARMS) for Rain-Fed Lowland Rice in Lao PDR

ISBN : 979-11-5698-203-6

Published in March 2018

Published by the APEC Climate Center

Produced by Kyungsung Media