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A framework for assessing the value of seasonal climate forecasting in key agricultural decisions

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ABSTRACT

While climate information services are widely available, translating climate information into actionable solutions to reduce climate risk, which are readily taken up by producers, remains a critical challenge. Here, we apply a bio-economic approach to assess the potential economic value of seasonal climate forecasts (SCFs) as a basis for climate services for use in agricultural decision-making. We use a case study approach, quantifying the impacts of seasonal precipitation on rice cropping, a dominant farming system in the Greater Mekong Region (GMR) in Southeast Asia. We demonstrate values of seasonal precipitation forecasts for a range of forecast skill levels from low to perfect skill for three seasonal precipitation conditions (wet, normal and dry), as well as extreme conditions (extreme wet and extreme dry). Based on our integrated bio-economic assessment and seasonal variation in precipitation, we identify an optimal rice sowing window, which potentially results in improved yield and economic benefits compared with the currently applied sowing window. Applying this approach using common rice varieties grown by farmers – specifically, the medium growth duration Jasmine rice and the short duration Vietnamese long grain white rice variety OM 5451 – we find significant value in using seasonal precipitation forecasts to identify optimal sowing windows, ranging from an average of \$135 ha^{-1} for precipitation forecasts at the current level (70% accuracy) of forecast skill to \$220 ha^{-1} for perfect (100% accurate) precipitation forecasts.

We propose that such a framework can be used to examine the value of using seasonal climate forecasts, even at current skill levels, in farm adaptive operational decision-making. We envisage that demonstration of the value of using seasonal forecasts in crop production system decisions will build user confidence and help in upscaling the use of climate information in the region and more broadly.

Practical implications

Increasing climate variability and extreme climatic events driven by climate change have negatively affected agricultural production in many regions of the world. While climate forecasts for the coming seasons and years are currently widely available and expected to be useful for the adaptation of agriculture to climate variability and change, a range of factors may limit the uptake of the forecasts in farm decision making. Factors such as forecast reliability (uncertainty), a lack of targeted forecasts that are fit for purpose, and farmers' perceptions are creating barriers between the adoption and application of forecast information in agricultural decision making. Kusunose and Mahmood (2016) identify the need to explicitly and realistically incorporate forecast uncertainty into forecast use frameworks as an essential step toward overcoming such barriers and as best practice for climate service development supporting adaptation decisions in agriculture. In the present work, we aim to provide an example of that best practice – specifically for sowing decisions in rice production systems in the Vietnamese Mekong Delta (VMD), one of the climate change hot spots of the world.

Adjusting the sowing date has been identified as an adaptive strategy to reduce the impacts of climate variability and climate change, and to enhance sustainable crop production (Lobell et al.,

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2015). Optimising sowing times enables the targeting of rice crop growth within a period of suitable climatic conditions (Zheng et al., 2012; Radanielson et al., 2019), mitigating the yield and economic impacts of adverse climatic events (Mushtaq et al., 2017; An-Vo et al., 2018). For rice-based cropping systems in the VMD, adjusting sowing dates has been highlighted as an immediate adaptation option (Bong et al., 2018). During the wet season cropping window, selecting the date for sowing is critical for rainfed rice farmers due to seasonal climate variability associated with the onset of the 6-month rainy season and associated increase in temperature and change in solar irradiance. Time of sowing is an important decision for a good cultivation outcome – if farmers sow too early, then there is a risk of low rainfall at the start of the crop's growth, while sowing too late might mean that the crop experiences reduced solar irradiance and increased temperature at the end of the growing season, potentially leading to crop yield decline.

This study develops a novel framework for using seasonal forecasts, which provides a method or tool that takes into account the forecast uncertainty of growing season precipitation in adaptive sowing decisions. We also investigate the potential value of using climate forecast information in decision making to enhance the resilience to climatic risk of rice production systems in the case study region. We anticipate that the framework for valuing climate services developed in this work can not only improve the adoption of seasonal climate forecasts for the adaptation of rice production to climate change in the Great Mekong Region, but also provide a pathway for enhanced use of seasonal forecasts to support decisions in rainfed agricultural production systems more broadly.

Specifically, the present valuation supports the need for targeted climate services in rice growing countries that are vulnerable to impacts from climate variability and climate change. It has the advantage of providing a reference baseline that is often lacking in climate service impact studies (Tall et al., 2018). Applying this framework in other rice growing areas that are vulnerable to climate variability (e.g. the greater Mekong delta and across Asia and Africa) would be very beneficial in facilitating the communication of climate information to farmers and supporting initiatives in climate adaptation, particularly where there are large uncertainties associated with climate forecasts (Tall et al., 2018). While case studies such as this are needed to establish the baseline information required to effectively communicate the value of climate information and enhance climate variability and climate change adaptation for more sustainable and resilient agri-food systems, the present valuation can also support decisions at government level to invest in improved regional and national weather station observation networks as well as research, development and extension programs. In addition, improvements in the skill of seasonal forecasts are still needed to increase forecast quality and thus achieve better economic and societal benefits of the forecasts locally and globally.

Introduction

The Greater Mekong Region (GMR) is home to more than 300 million people in Southeast Asia, many of whom are smallholder farmers. The region's predominantly small-scale agricultural systems are characterised by low crop production (Kijne et al., 2009). The majority of these small-holder agricultural systems are constrained by problems of soil erosion, poor soil fertility and climate variability (Schiller et al., 2001). A significant challenge in the GMR over coming decades will be to increase food security in the face of climate change and an associated declining productivity of land and water resources (UN ESCAP, 2009).

The Vietnamese Mekong Delta (VMD or the Delta; Fig. 1) is especially important for rice cropping, accounting for more than half of the domestic rice production and approximately 90% of annual rice exports from Vietnam, a leading rice exporter. Nevertheless, due to climate change (and associated changes in seasonal climate, increasing climate variability and adverse climate conditions, sea level rise and salinity intrusion) and upstream hydropower development (resulting in upstream water retention), rice farming in this region faces increasing levels of environmental stress and water related constraints. This is particularly the case for rain-fed rice production, which depends on seasonal rainfall. As a result, there has been increasing demand for sustainable 'soft' measures (Smajgl et al., 2015) such as new technologies, adaptive decision-making and improved crop management practices for rice farming in the region (Phan et al., 2018; Clauss et al., 2018; Paik et al., 2020). However, there remains very limited development and awareness of climate services for sustainable rice farming in the Delta; that is, the provision of climate information designed to assist in

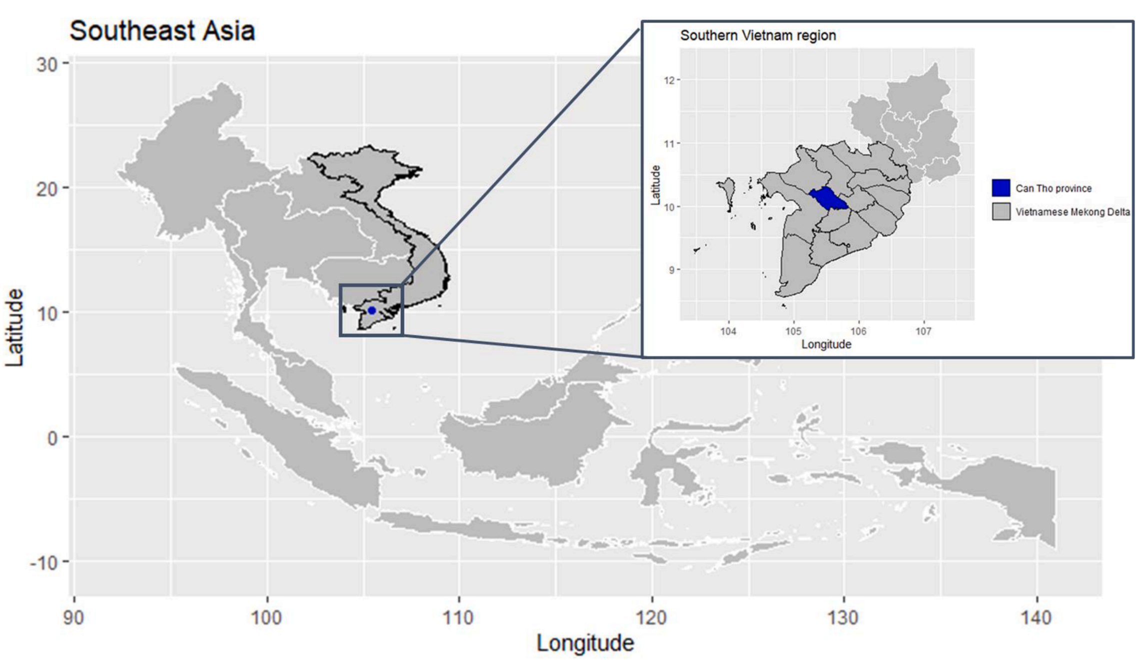

Fig. 1. Map of the southern Vietnam region showing the position of Can Tho province within the Vietnamese Mekong Delta.

on-farm decision-making (Buontempo and Hewitt, 2018).

Rice cropping is highly susceptible to changes in climate because of its high water requirements and there are a number of studies examining the impacts of climate variability on rice production. Sakamoto et al. (2006) investigated the relationship between seasonal change in the flow regime of the Mekong River, the spatio-temporal distribution of cropping systems and rice phenology. Koide et al. (2013) developed regression models for national rice production in the Philippines using various climate variables as predictors; the added value of using General Circulation Model (GCM) forecasts in crop yield forecasting was also estimated relative to purely empirical models. Chung et al. (2015) studied the impacts of seasonal climate variability on rice production in the Central Highlands of Vietnam. In addition, relationships between rice agronomy and climate are well documented (e.g. Lansigan et al., 2000; Naylor et al., 2001; Selvaraju, 2003; Lansigan, 2005; Dawe et al., 2006; Roberts et al., 2009).

For rice-based cropping systems in the VMD, Bong et al. (2018) assessed a number of adaptation options and highlighted adjusting sowing dates as an immediate measure. During the wet season cropping window, selecting the date for sowing is critical for rain-fed rice farmers due to seasonal climate variability associated with the onset of the 6-month rainy season and associated increase in temperature and change in solar irradiance (Fig. 2). Time of sowing is an important decision for a good cultivation outcome – if farmers sow early, there is a risk of low growing seasonal rainfall (in-crop seasonal rainfall) while, with late sowing, the crop might experience a reduction in solar irradiance and increase of temperature at the end of the growing season (Fig. 2) potentially leading to crop yield decline.

Seasonal climate conditions are significant drivers of agricultural production especially for rain-fed farming systems (Hansen, 2005; Cooper et al., 2008; Nidumolu et al., 2015). Information from seasonal climate forecasts (SCFs) can thus support timely decision making on farms to reduce climate risk and improve farm productivity and profitability (Hammer et al., 2000). However, lack of evidence on the economic value of using SCFs and lack of guidance and demonstration of how to use forecast information have limited the use of SCFs in climate risk management decision-making on farms worldwide (Klemm and McPherson, 2017; An-Vo et al., 2019a). Although available climate forecasts have less than perfect predictive ability (Klemm and McPherson, 2017), they may still have potential value in informing decisions such as the optimal timing of sowing dates and choice of crop sequencing. This is particularly the case in climatically variable regions such as the VMD and for farming systems, such as rice cropping, where production is sensitive to extreme weather conditions such as heavy rainfall and lack of precipitation. Timing of rice crop establishment can determine the system productivity in terms of yield and water use among others (Balwinder-Singh et al., 2015; Ding et al., 2020). Late onset of the wet season generally delays crop establishment and thus extends the crop growth period, increasing the risk of terminal (end of growing season) drought, which is becoming more frequent with the influence of El Niño seasonality (Naylor et al., 2001). A delay in the wet season can also lead to later sowing of the next crop and may, in some areas, preclude the sowing of a subsequent dry season crop (Ahmed et al., 2014; Naylor et al., 2001, 2007), putting at risk overall crop production at the farm level with potential larger scale impacts on local and regional food security.

'When to sow' is a key decision made to reduce climate risk in rain-fed rice cropping systems. While seasonal precipitation forecasts are among the most available climate services to farmers, often the focus is on the likelihood of a dry or wet cropping season and of associated extreme events such as drought or flood (Hammer et al., 1996). This information is often considered as binary (i.e. happening versus not happening) by farmers and frequently used to explain the outcomes of a season, such as crop failure and good or poor yield (Roudier et al., 2014), rather than as a tool to enable adaptive decision-making in light of the information provided by the forecasts. Forecast accuracy has been among the key factors limiting the use of SCFs in decision-making by farmers. SCFs with far from perfect skill (and poor understanding of uncertainty) have had a detrimental effect on farmers' trust in climate information and thus climate services. Existing efforts in the extension of seasonal climate information focus on building the capacity of farmers and extension agents to better understand and apply the data presented with SCFs, but lack a robust framework by which potential gain in using these in farm decision making, even at current levels of forecast

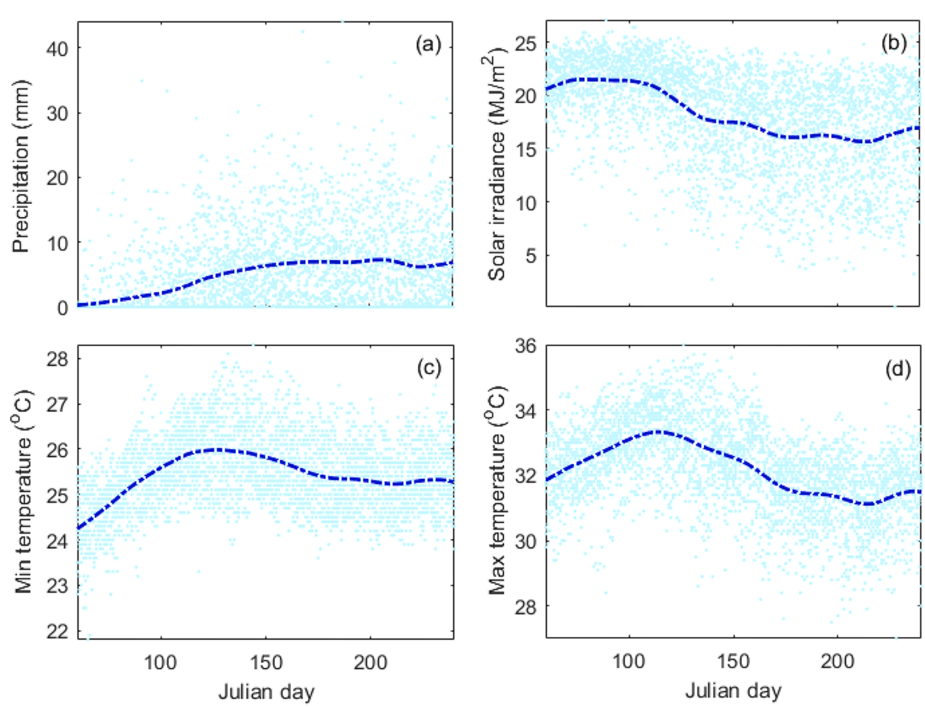

Fig. 2. Observed data of climate variables representative of the climatic environment in Can Tho Province over the last 32 years. The dashed lines represent long-term smoothed average values.

accuracy, can be assessed.

In the present work, we have developed a first of its kind framework that will enable these evaluations by establishing the economic benefit of applying SCF information in sowing decisions in rice cropping for different levels of SCF skill. In addition to other adaptive management strategies, accounting for SCFs in rice crop sowing decisions has potential to reduce risks due to climate variability and change in rain-fed systems and ensure higher yields. Here, we demonstrate the usefulness of SCFs in rain-fed rice production systems in the Delta for a case study located in Can Tho Province, Vietnam (Fig. 1), accounting for the inherent uncertainty in the forecast system, and provide evidence to support better communication of climate services benefit. We first analyse seasonal climate (rainfall) data and its impact on seasonal rice yield variability and profitability. An integrated seasonal forecasting framework is then developed, which includes a novel parameterisation for the errors of less than perfect (i.e. < 100% accurate or 'imperfect') dynamic forecasting systems; calibrated rice cropping model simulation; and a proposed economic value assessment with decision analytic. The proposed end-to-end seasonal forecasting framework – the processing of available SCFs (one end) to identify an optimal sowing date (decision analytic, another end) for improving the economic return – shows considerable economic benefits of using seasonal climate forecasts.

Sowing decisions in wet season rice cropping

Rainfall regimes in the southern region of Vietnam including the Mekong Delta are mainly controlled by summer monsoons and tropical disturbances, as well as local conditions such as topography (Phan-Van et al., 2018). The annual rainfall regime of the region is divided into two distinct seasons: the rainy or wet season (from May to October) and the dry season (from November to April of the next year). Rainfall during the rainy season normally accounts for about 80% of the total annual rainfall (Nguyen et al., 2014) and the region is thus suitable for rain-fed rice cropping. However, there is also significant seasonal variation in the amount and timing of rainfall through time, largely driven by a strong association in seasonal rainfall in Vietnam with the El Niño Southern Oscillation (ENSO) and other large-scale dynamic oceanic-atmospheric processes (Gobin et al., 2016; Nguyen et al., 2019). For example, drier conditions occur when average sea surface temperatures (SSTs) over the Central Pacific Niño-3.4 region are warmer, and *vice versa* (wetter when average Niño-3.4 region SSTs are colder) (Nguyen et al., 2019).

In the VMD, wet season rice cropping generally runs from March to August. The start of the cropping season is largely determined by the feasibility of land preparation, which is a function of the timing of the previous crop harvest, the onset of the monsoon and the leaching of salinity caused by salt intrusion from the ground water table during the dry season (Wassmann et al., 2019). Following land preparation, the optimum sowing date is determined by climatic conditions. The rainfall pattern before sowing governs soil moisture at sowing, influencing crop establishment, following which dry spells or heavy rainfall can be detrimental, especially during the early growth stage of the crop. Farmers will benefit where a sowing window can be defined that minimizes such risks as well as exposure to end of season drought and heat stress. In addition, a growing period that has higher radiation, sufficient rainfall, and optimum temperature conditions will favour higher yield, increasing revenue (Evans and De Datta, 1979; Deng et al., 2015).

Methodology

In this work, we investigate whether seasonal climate data analysis can be used to identify a sowing window that can reduce the risk of crop production losses and deliver greater benefit to rice farmers in the VMD. We focus on growing season precipitation (GSP), which we define as the total accumulated precipitation from the sowing date to harvesting date. For each potential sowing date, we also define different seasonal climate conditions for crop growth based on the historical GSP variability, including climatological, extreme and moderate conditions. The climatological condition or 'climatology' indicates the average of the historical GSP over the selected period. Seasonally extreme conditions are defined, with an 'extreme wet' condition indicating the top 10% of the historical GSP while an 'extreme dry' condition indicates the bottom 10% of the historical GSP. The middle 80% between the extreme wet and extreme dry conditions indicates a non-extreme condition. For seasonally moderate conditions, a 'moderate wet' condition indicates the top 33% of the historical GSP while a 'moderate dry' condition indicates the bottom 33% of the historical GSP. The middle 33% between the moderate wet and moderate dry conditions indicates a 'normal' condition. Our aim is to then economically evaluate the use, in rice sowing decisions, of seasonal precipitation forecasts of both moderate (Table 1) and extreme (Table 2) conditions. Rice crop performance based on average climatological conditions was employed as a baseline, effectively representing the case with no added knowledge from a forecast of how the climatic conditions might vary from average.

Rice yields for early wet season cropping under the defined seasonal climatic conditions were simulated for each sowing date in the current sowing window (from March to May) using the calibrated rice crop model ORYZA v3 (Li et al., 2017). We then employed an expected profit approach to determine the optimal sowing date achieving the highest profit under each of the considered climatic conditions. Potential economic values of using imperfect SCFs in rice crop decision making (specifically, sowing date decisions), taking into account forecast uncertainty for each moderate or extreme condition, were quantified by a value assessment framework, providing different optimal sowing date decisions associated with the different forecasts relative to that of climatology (i.e. decision-making without forecasts); the optimal date in each case was identified as the date with the maximum simulated expected gross margin for the crop.

Forecast quality parameterisation for dynamic forecasting systems

Given the uncertainty inherent in seasonal climate forecasts (Klemm and McPherson, 2017) we also assessed the value of using <100% accurate (i.e. imperfect) seasonal precipitation forecasts in selecting optimal sowing dates for each category of forecast. To do this, we first assessed the quality or skill of the seasonal forecast system to determine the probability that it will be in agreement with (i.e. predict) the eventually observed seasonal conditions for a growing period. We then used the quality of the forecasts to parameterise the (imperfect) structure of available seasonal precipitation forecasts, thereby accounting for forecast uncertainties.

Forecast quality has been typically evaluated for a study site using hindcast data (Kusunose and Mahmood, 2016; An-Vo et al., 2019b). The possibility or probability of the growing season precipitation condition can be represented by the forecast quality parameters (An-Vo et al., 2019a, 2019b) which, for dynamic forecasting systems, vary according to the issuing date of a seasonal precipitation forecast. It should be noted that the capacity of available dynamic forecast systems (e.g. ECMWF – seasonal forecast system 5; NCEP – Climate Forecasting System version 2; UK Met Office – GloSea5; JAMSTEC – SINTEX-F) to provide seasonal

Table 1
Moderate forecast system – forecast quality structure for imperfect forecasts of growing season precipitation tercile issued on date *I*, including moderate wet (W), normal (N) and moderate dry (D) seasonal conditions.

Forecast issuing date	Forecast	Outcome		
		W	N	D
I	W	$q_1(s)$	$\frac{2}{3}[1-q_1(s)]$	$\frac{1}{3}[1-q_1(s)]$
	N	$\frac{1}{2}[1-q_2(s)]$	$q_2(s)$	$\frac{1}{2}[1-q_2(s)]$
	D	$\frac{1}{3}[1-q_3(s)]$	$\frac{2}{3}[1-q_3(s)]$	$q_3(s)$

Table 2
Extreme forecast system – forecast quality structure for imperfect forecasts, issued on date *I*, of extreme growing seasonal precipitation including extreme wet (EW), non-extreme (NE) and extreme dry (ED) seasonal conditions.

Forecast issuing date	Forecast	Outcome		
		EW	NE	ED
I	EW	$q_1(s)$	$\frac{8}{9}[1-q_1(s)]$	$\frac{1}{9}[1-q_1(s)]$
	NE	$\frac{1}{2}[1-q_2(s)]$	$q_2(s)$	$\frac{1}{2}[1-q_2(s)]$
	ED	$\frac{1}{9}[1-q_3(s)]$	$\frac{8}{9}[1-q_3(s)]$	$q_3(s)$

climate forecasts that are updated regularly throughout a season is increasing. The structure of a seasonal precipitation forecast, including its error distribution, can also be derived for each issuing date (*I*) (Tables 1, 2). In this study, we distinguished forecasts from outcomes, whereby a forecast indicates the growing season precipitation that we wanted to predict before or at the sowing date (i.e. the predicted precipitation of the growing season before the season started), while an outcome indicates the growing season precipitation realized at the end of the season (i.e. the actual precipitation recorded over the season). Forecast quality parameters – q_1, q_2, q_3 – represent post agreement rates of forecasts issued on a date I in predicting moderate or extreme wet, normal or non-extreme, and moderate or extreme dry growing seasonal precipitation, respectively (Tables 1, 2). Post agreement rates are rates of correct forecasts similar to those for statistical forecasts (An-Vo et al., 2019a, 2019b); in the present work, these are transient functions of both the forecast issuing date I and sowing date s (Tables 1, 2).

For a moderate forecasting system (Table 1), error distribution was typically assumed to be uniform among the failed outcomes (e.g. Kusunose and Mahmood, 2016). An-Vo et al. (2019b), however, point out that for precipitation tercile forecasts such an assumption is only acceptable for a normal (N) forecast (second row) and not for a moderate wet (W) or a moderate dry (D) forecast. Our analysis of recorded long-term precipitation data at stations shows that error distribution of a seasonal forecast system varies spatially. Error distributions of the moderate (extreme) wet and moderate (extreme) dry forecasts, respectively, such as those in the first and third rows of Table 1 (Table 2), respectively, are more sensible based on our analysis for recorded long-term precipitation data at stations in the studied region.

Integrated bio-economic modelling with historical climate data

Climate data

Gridded daily climate data for the case study site were used (NASA, 2019). These data include maximum and minimum temperatures (°C), solar radiation (MJ m^{-2} d^{-1}), wind speed (m s^{-1}), and relative humidity (%) covering the 32-year period from 1985 to 2016. Correlation analysis was performed between these data and the observed daily climate data of the period, 1998 to 2016. Correction coefficients were then defined to minimise deviation of the gridded data from the observed data for temperature and radiation at the case study site (supplementary Fig. S1, relative root mean square error (RMSEn) $< 10\%$) to generate the data covering the period from 1985 to 1998. For precipitation, data from the gridded precipitation database developed by Nguyen-Xuan et al. (2016) was used from the period 1985 to 1998.

Rice yield simulation

The rice crop model ORYZA v3 (Li et al., 2017) was used to simulate rain-fed rice yield under different seasonal climatic scenarios. This is an established validated model used in simulating rice crop growth and yield, particularly under the rice production environment of Vietnam (Tuong et al., 2013; Li et al., 2017; Stuart et al., 2016). It is an ecophysiological model using a daily time step representation of rice crop development, growth and yield in interaction with environmental and crop management conditions. Crop development is simulated daily, considering its responses to temperature and photoperiod. Similarly, daily crop biomass is simulated as a result of radiation interception and CO_2 assimilation, which also respond to climate conditions and soil water and nitrogen availability (Bouman et al., 2001; Bouman and van Laar, 2006; Li et al., 2017). Rice yield is simulated from biomass accumulation during crop growth allocated to the grain from the panicle initiation stage to maturity.

The model was calibrated and validated using on farm data, as reported by Stuart et al. (2016); Stuart et al. (2018). Relative root mean square error between the observed and simulated yield was lower than 10% (RMSE $=$ 652 kg ha^{-1}, RMSEn $=$ 9.05%) and within the range of standard deviation of reported yield measurements in experimental fields. This level of uncertainty is typical in yield estimates using rice models (Li et al., 2015; Gaydon et al., 2017; Radanielson et al., 2019).

In this study, the model was run to simulate rice cropping with optimum application of fertilizer following the best management practices recommended for the study area and with pest and disease control minimising yield losses. A daily sowing date interval was then considered for scenario simulations, covering the period from 1985 to 2016, for two varieties commonly grown by farmers in the study site: a medium duration variety (c.v. Jasmine) and a short duration variety (c.v. OM5451). Both varieties are among the most used varieties by farmers in VMD (Devkota et al., 2019; Stuart et al., 2018). The medium duration (105–115 days) variety is mostly grown in the dry season and sown between November to December, when climatic yield potential is higher and climatic risk is reduced. Medium duration varieties may be used in the wet season in areas where double cropping is practiced (i.e. two rice crops are produced in a year). The short duration (95–100 days) variety is mostly grown in the wet season with a sowing window from March to May, allowing establishment of a third crop as a late wet season crop. Use of short duration varieties is among the recommended adaptation strategies to climate variability in rainfed system as it allows flexibility in terms of the cropping window and potential to escape periods of high risk for temperature stress and extreme rainfall conditions (both heavy rainfall and moisture deficit). In the present study, crop model parameters characterizing these two varieties were calibrated and validated for southern Vietnam, as in Stuart et al. (2016). We ran 50,000 simulations to simulate rice crop yield for the two varieties under rain-fed conditions for the 32-year period from 1985 to 2016.

Integrated bio-economic assessment

We then employed a bio-economic model which integrates the grain yield simulated by the rice crop model ORYZA (v3) with profit functions to derive gross margin versus yield relationships by systematically varying sowing dates under the different seasonal climate forecast categories. The profit function of the rice crop represents the net return after subtracting production costs from income under different climatic conditions, as given by

$$\Pi(s) = p \times Y(s) - C \tag{1}$$

where $\Pi(s)$ is the profit function and $Y(s)$ the associated yield production function, which are themselves functions of the decision on sowing date s under the defined seasonal climate conditions; p is the sale price of paddy rice grain and C is the production cost including the costs of seed, nursery, fertiliser, herbicide, pesticide, land preparation, crop establishment, harvesting, threshing, cleaning and drying (estimated at \$461 ha^{-1} for rain-fed rice cultivation in Can Tho (Devkota et al., 2019)). The sale prices of paddy rice are average monthly prices for twelve months in 2019 collected from AGROINFO (www.agro.gov.vn, accessed 10/01/2020); these were \$225 t^{-1} and \$220 t^{-1}, respectively, for medium (Jasmine) and short (OM 5451) growth duration rice varieties.

Decision analytic and value assessment

The sowing window considered in the present study is from 1st of March to 31th of May – the currently applied sowing window for early wet season rice cropping in the VMD. We consider a forecast f for the period starting from the 1st of March, issued earlier or at the 1st of March; hence, the forecast issuing date I (Tables 1 & 2) is the 1st of March or earlier. Our aim here is to determine the optimal sowing date in the sowing window given the issued forecast by the following proposed decision analytic. This proposed decision analytic can be implemented in a similar manner for forecasts issued on any day within the sowing window for the period following that day.

We also assume that the farmer is risk neutral – a commonly assumed risk preference in forecast use analysis (Mjelde et al., 1993; Meza et al., 2008; Moeller et al., 2008; Kusunose and Mahmood, 2016); i.e. he/she would choose the decision that results in the highest expected profit, conditional on the forecast. Literature related to rice growers in Asia risk attitude, generally, points towards a risk-averse attitude (see Lucas and Pabuayon, 2011; Pham and Waibel, 2018); they thus likely implement strategies based on highly skilful seasonal climate forecasts. For the forecast f, the expected profit of any one sowing decision on a date $s$within the sowing window is given by

$$E[\text{profit}|f = i, s] = \sum_j prob(o = j|f = i)\frac{1}{T_j}\sum_{k=1}^{T_j}\Pi_k(s, j) \tag{2}$$

where $i \in \{\text{W, N, D}\}$ or $\{\text{EW, NE, ED}\}$ is the forecast set and$j \in \{\text{W, N, D}\}$ or $\{\text{EW, NE, ED}\}$ is the corresponding outcome set, o denotes one of the outcomes, $T_j$is the number of historical climate years having an outcome j, and $\Pi_k(s, j)$ is the economic return in year k as a function of the decision in each of the outcome categories. The economic return in each year is a gross margin estimate based on the yield simulated by the ORYZA model. We consider the optimal decision recommendation as follows.

Given the crop variety and an issued imperfect forecast i, the farmer might want to know which sowing date would result in the best expected profit. The farmer's best sowing date selection $s^*{}_i$ given the i forecast is

$$s^*{}_i = \underset{s\in S}{max}E[profit|f = i, s] \tag{3}$$

where **S** is the considered sowing window. For an imperfect moderate forecast system, as presented in Table 1, using the imperfect moderate wet forecast as an example, we can expand Eq. (2) to find the expected profit for a sowing date s:

$$E[\text{profit}|f = \text{W},\ s] = q_1(s)\frac{1}{T_\text{W}}\sum_{k=1}^{T_\text{W}}\Pi_k(s, \text{W}) + \frac{2}{3}[1 - q_1(s)]\frac{1}{T_\text{N}}\sum_{k=1}^{T_\text{N}}\Pi_k(s, \text{N}) + \frac{1}{3}[1 - q_1(s)]\frac{1}{T_\text{D}}\sum_{k=1}^{T_\text{D}}\Pi_k(s, \text{D}) \tag{4}$$

Similarly, we can estimate expected profits for the sowing date s given the other imperfect forecasts or for other sowing dates within the given forecast set. For an extreme wet forecast or an extreme dry forecast, Table 2 can be similarly employed in Eq. (2).

The value of imperfect forecasts (and therefore also the value of any future increases in forecast quality) is the difference in profit achieved from the farmer's optimal responses in the presence of forecasts (or 'better' forecasts) relative to the profit achieved from the farmer's optimal responses to the climatological condition (or a reference forecast). We acknowledge that a farmer's perception of the upcoming seasonal climate based on recent past experience is typically better than the climatological condition. In this case, the baseline profit estimation based on the climatological condition in the present work might be smaller than what would be expected in practice, resulting in slightly higher estimation of forecast values (An-Vo et al., 2019b). To determine the farmer's optimal response to the climatological condition (climatology), we assume that the farmer would have chosen a sowing date $\widehat{s}^*$ that solves the following problem:

$$\widehat{s}^* = \underset{\widehat{s}\in S}{max}E[profit|\widehat{s}] \tag{5}$$

where

$$E[\text{profit}|\widehat{s}] = \sum_j prob(o = j)\frac{1}{T_j}\sum_{k=1}^{T_j}\Pi_k(\widehat{s}, j) \tag{6}$$

The values of various imperfect forecasts are the differences in expected profits between the optimal dynamic strategies employing the forecasts (i.e. changing with the forecasts) and the optimal static strategy in response to the climatology (i.e. not changing with the forecasts). For a forecast i and a sowing date s, we have forecast value $FV(i, s)$ given as

$$FV(i, s) = |E[profit|f = i, s^*{}_i] - E[profit|f = i, \widehat{s}^*]\,| \tag{7}$$

It can be seen from Eq. (4) that $FV(i, s)$ also depends on the forecast quality of the imperfect forecasts. We can estimate the values of the various forecasts for the sowing decision across a range of forecast qualities from no skill to a perfect forecast (with 100% skill) to quantify the values of increasing (i.e. improvements in) forecast quality.

Results

In-crop seasonal precipitation increased almost linearly from the start of the sowing window (early March), stabilising around the third and fourth weeks of April (Julian date 110 and 120), respectively, for both medium and short growth duration varieties (Jasmine and OM 5451) and with remarkable impacts on simulated crop yields (Fig. 3). Strong correlations were evident between in-crop seasonal precipitation and crop yields (0.95 for climatological condition) for both varieties (Table 3), indicating that seasonal precipitation is a major yield driver of productivity for rain-fed rice. It is noteworthy, however, that the correlations were considerably weaker for extreme conditions (Table 3). Weaker correlations in extreme conditions here – especially the extreme wet condition – might be due to uneven rainfall distribution throughout the crop growth season such as the dry spells occurring after 15 days from sowing (Fig. S2).

Identifying better sowing dates offer remarkable yield benefits

Due to the critical seasonal climate variability of the early wet rice cropping season, sowing date was found to have a significant impact on in-crop seasonal rainfall and variability, and especially the rice yield outcomes in terms of expected (average) yields and associated yield variabilities (Fig. 3). For instance, for crops sowed in early March, expected yields of around 3 and 2 t ha^{-1}, respectively, were achieved for the medium (Jasmine) and short (OM 5451) duration varieties, while expected yields more than doubled (to more than 6 and 4 t ha^{-1}, respectively) when these varieties were sowed in April. On this basis of simulated expected (average) yields for each sowing date, a recommendation to farmers in the case study region to implement a sowing window from the first week of April to mid-May (Julian dates 100 to 140) is indicated. This recommended sowing window is narrower than the current sowing window (from March to May) implemented by farmers in the case study region. Notable yield variability could also be seen for each sowing date ranging from 3 to 6 t ha^{-1} for the medium (Jasmine) and from 2 to 4 t ha^{-1} for short (OM 5451) duration varieties (Fig. 3a & b, respectively). Depending on particular seasonal climate condition, high yields (up to 8 and 6 t ha^{-1}, respectively, for the medium and short duration varieties) could also be achieved by sowing in March.

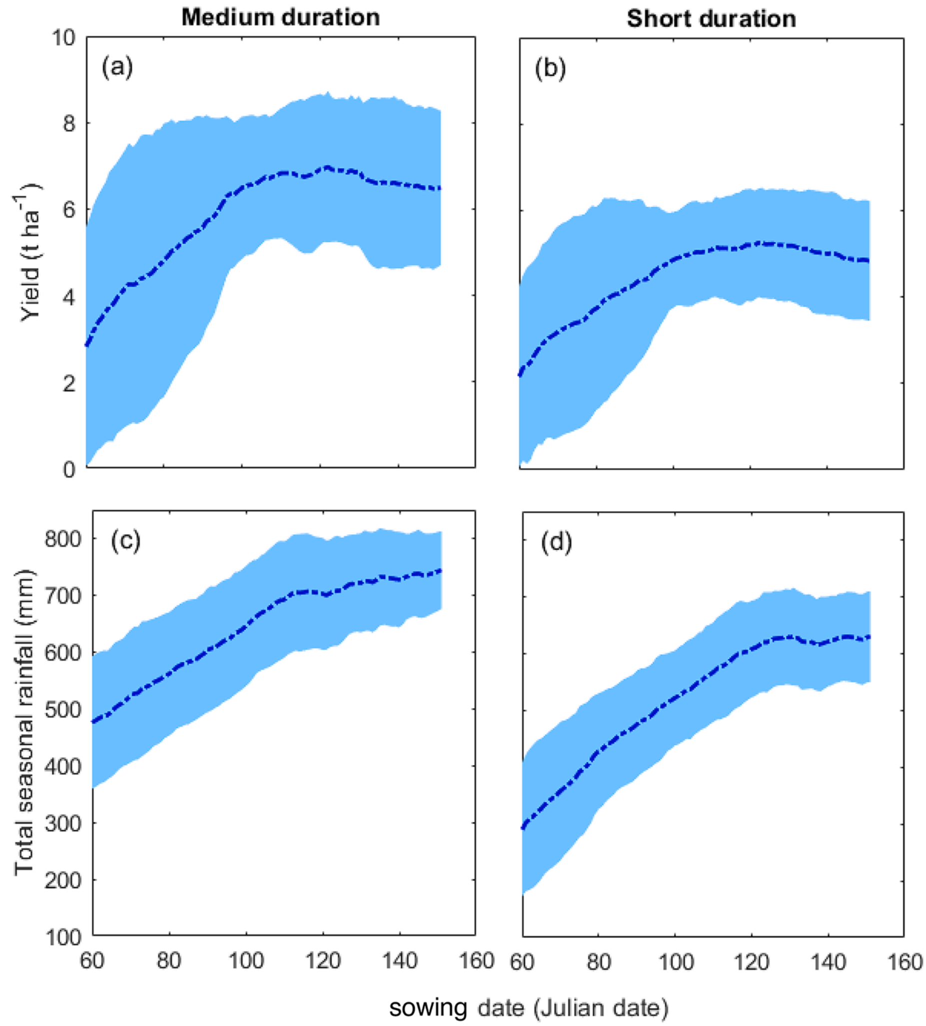

Fig. 3. Crop yield simulation results for (a) the medium growth duration (Jasmine) and (b) the short growth duration (OM 5451) rice varieties, including mean crop yields and their variability (1 standard deviation intervals) for the current sowing window from 1st March to 31th May. Corresponding mean in-crop seasonal precipitations and their variability (1 standard deviation intervals) are also presented (c & d).

Table 3
Correlations between in-crop seasonal precipitation and crop yield for the current sowing window under different seasonal climatic conditions. * indicates statistical significance with $p < 0.001$.

Variety	Extreme wet	Moderate wet	Climatological condition	Moderate dry	Extreme dry
Jasmine	0.51*	0.97*	0.95*	0.92*	0.79*
OM 5451	0.49*	0.92*	0.95*	0.93*	0.92*

These results suggest that, if seasonal climate information/data can be effectively analysed and used to support farmers making toward optimal sowing decisions, rice crop productivity and profitability can be significantly improved. We demonstrate below the best sowing date determination based on the expected profit approach given imperfect seasonal precipitation forecasts. Maximising profit is considered more important for farmers than solely maximising yield *per se*, even though the results only differ when costs vary (An-Vo et al., 2018).

Significant economic values of seasonal precipitation forecast

Significant seasonal precipitation variability in the case study region can also be represented by the differences in its mean and variability within each moderate seasonal precipitation condition (Fig. 4). Here, it can be seen that the average in-crop seasonal rainfall (and its variability) for each sowing date differs significantly between moderate wet (W), normal (N), and moderate dry (D) cropping seasons. For the medium duration rice variety (Jasmine), between 150 and 300 mm additional seasonal precipitation is received under normal and moderate wet conditions, respectively, relative to the moderate dry condition for the current sowing window. For the short duration rice variety (OM 5451), these figures are 100 and 200 mm, respectively. Such differences in in-crop seasonal precipitation can potentially drive significant differences in crop yield and economic outcomes for the three climatic conditions.

Expected gross margins also differ between the moderate seasonal precipitation forecasts for both medium duration and short duration rice varieties, depending on forecast quality (Fig. 5). Using the current sowing window from 1st March to 31th May, relatively little difference was found in the gross margin of more skilful forecasts of normal conditions (Fig. 5c & d); however, our analysis indicates distinct gross margin benefits for both wet and dry forecasts (Fig. 5a, b, e & f) compared to that of the climatological condition (i.e. no forecast). Expected gross margins of moderate wet forecasts also generally increase with improving forecast quality, from 50% accuracy to a perfect (i.e. 100% accurate) forecast, while those of dry forecasts decrease. In cases of perfect forecasts ($q_1 = q_3 = 1$), expected gross margins for both moderate wet and moderate dry forecasts may differ by more than $500

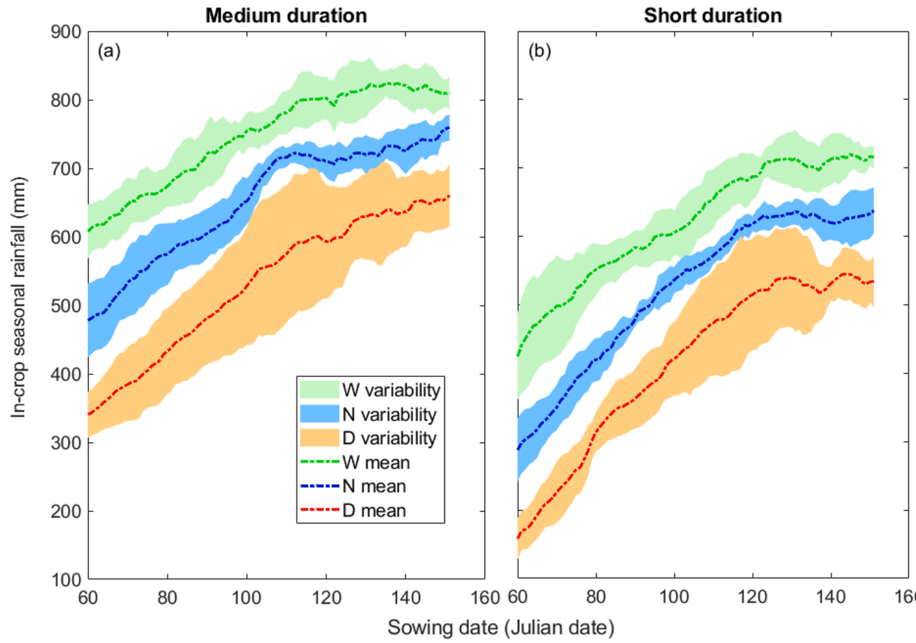

Fig. 4. Moderate in-crop seasonal precipitation conditions for (a) a medium growth duration (Jasmine) and (b) a short duration (OM 5451) rice variety in the current sowing window, including means and corresponding variabilities (±1 standard deviation). Note that OM 5451 is a shorter duration crop variety and thus its cumulative in-crop seasonal precipitation values are less than those of for the medium duration Jasmine variety.

ha^{-1} compared to those of the seasonal climatological condition based on early sowing dates for both medium and short duration rice varieties. These trends were found to be even more significant for extreme forecasts (Fig. 6), where a perfect extreme wet forecast might result in an increase in the expected gross margin for the medium growth duration Jasmine rice of more than $1000 ha^{-1} compared to those of the climatological condition for the same early sowing dates (Fig. 6a).

Figs. 5 and 6 also, importantly, indicate that the seasonal precipitation forecasts tested here can identify optimal sowing dates for each variety; in most cases these differ substantially from those of the climatological condition. For moderate wet (moderate dry) forecasts, optimal sowing dates are later (earlier) than those selected based on average climatological conditions (i.e. an equal chance of wet, normal or dry conditions). Increasing forecast skill levels provide further evidence of value in using seasonal climate forecasts to inform management decisions, even where this information is imperfect (Fig. 7; also see Fig. S3 for seasonal extreme precipitation forecasts).

By identifying different optimal sowing dates for the different forecasts, which may be perfect or imperfect, we can now quantify the economic values of the forecasts accordingly – which are the differences between the maximal expected gross margin of a forecast and the expected gross margin of that forecast at optimal sowing date of the climatology (without the forecast) (equation (7)). Using seasonal precipitation forecasts of moderate conditions for a rice production system with a medium growth duration variety such as Jasmine, significant average values of $87 ha^{-1} and $80 ha^{-1} can be achieved with the perfect moderate wet forecast (Fig. 8a) and the perfect moderate dry forecast (Fig. 8c), respectively. At current levels of forecast quality (around 70% accuracy), these values are, on average, $25 ha^{-1} and $35 ha^{-1} for the imperfect moderate wet forecast (Fig. 8a) and the imperfect moderate dry forecast (Fig. 8c), respectively. Forecast values for seasonal extreme precipitation forecasts (Fig. 9) are larger. For instance, the value of a perfect extreme dry seasonal forecast is $100 ha^{-1} (Fig. 9c).

Using seasonal precipitation forecasts of moderate conditions for the rice production system for the short duration variety OM 5451, we find that significant values of $63 ha^{-1} and $100 ha^{-1} can be achieved with the perfect moderate wet forecast (Fig. 8a) and the perfect normal forecast (Fig. 8b), respectively. With current levels of forecast quality (around 70% accuracy), these values are $30 ha^{-1} and $50 ha^{-1}, respectively, for the moderate wet (Fig. 8a) and normal (Fig. 8b) forecast. The finding that economic values of the imperfect and perfect moderate dry forecasts are relatively small is because the optimal gross margins achieved for the forecasts do not deviate much from those achieved at the optimal sowing date based on climatological information (Fig. 5f). However, forecast values of extreme seasonal precipitation forecasts (Fig. 9) are much greater, with values of $220 ha^{-1} and $155 ha^{-1}, respectively, for the perfect extreme wet (Fig. 9b) and perfect extreme dry (Fig. 9d) seasonal forecasts.

Discussion

The adoption of new technologies aimed at supporting decision making in farming systems depends on clear evidence of relevance to the decision-making processes of farmers and its ready availability and accessibility in an immediately usable format (Antle et al., 2017). We have developed here a novel approach that translates seasonal climate forecasts into actionable information for farmers to facilitate adaptation to climate variability and change. The climate services valuation framework developed in this work provides a pathway for enhanced use of seasonal forecasts in key climate sensitive cropping decisions.

Seasonal climate forecast and rice crop optimum sowing date

Climate variability and extreme climatic events are expected to increase in the Vietnamese Mekong Delta region, with significant negative impacts on farming systems dominated by rice production (Lacombe et al., 2012; Mainuddin et al., 2010; Kontgis et al., 2019). Adjusting the sowing time has been identified as an adaptive strategy to reduce the impacts of climate change and enhance sustainable crop production (Lobell et al., 2015). Optimal sowing time enables the targeting of rice crop growth within a period of suitable climatic conditions (Zheng et al., 2012; Radanielson et al., 2019), mitigating the yield and economic impacts of adverse climatic events (Mushtaq et al., 2017; An-Vo et al., 2018). Wet season rice crops in the Mekong delta are generally sowed in mid-March, but sowing dates vary amongst farmers and can range from early March to May (Stuart et al., 2018).

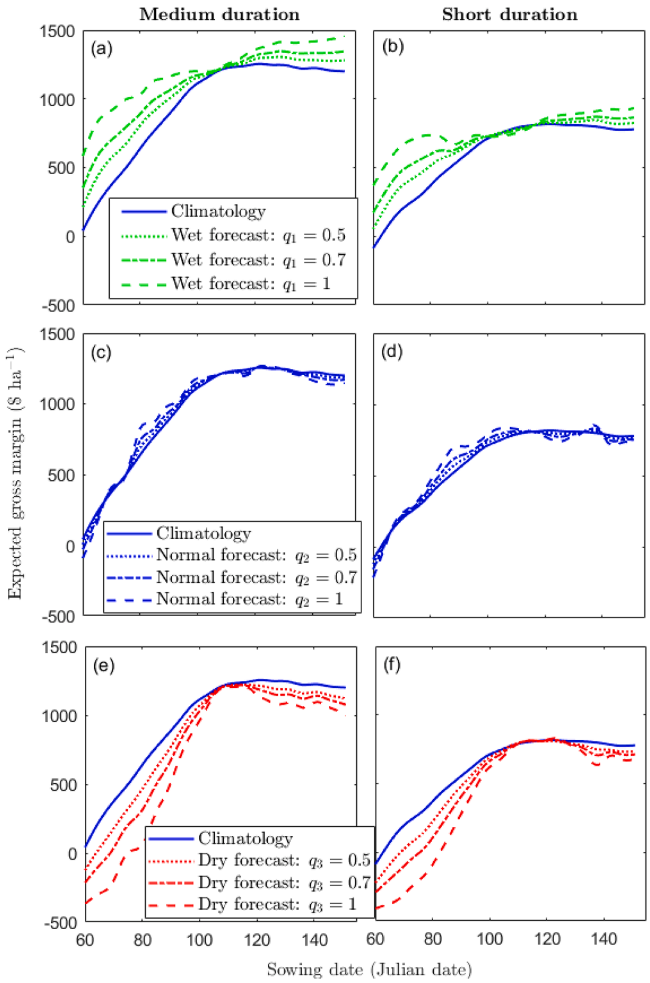

Fig. 5. Expected gross margins for different sowing dates for medium growth duration (Jasmine, left) and short growth duration (OM 5451, right) rice varieties for moderate wet (a & b, respectively), normal (c & d, respectively) and moderate dry (e & f, respectively) forecasts at three levels of forecast quality (i.e. skill). Climatological results (continuous lines) are presented for reference.

Here, we have demonstrated that rice crop yields in wet years are generally higher than those in normal and dry years, and also that average yield simulated over a period of 32 years is not representative of the yields achieved in extreme dry and extreme wet years. We also demonstrate that, while the onset of the sowing window used to achieve maximum yield under different classes of years was the same and relies generally on the onset of rainfall, the duration of the optimum sowing window to achieve maximum yield differs in wet and dry years. Differences in the optimal sowing window were observed among various seasonal climatic conditions between the two rice varieties included in this study. We have demonstrated that sowing windows for optimum productivity were wider with better seasonal precipitation (from < 10 days in dry years to up to 30 days in wet years). In dry years, late crop establishment beyond the optimum sowing window led to yield losses, likely associated with insufficient water availability to meet crop water demand (Tuong and Bouman, 2003; Wang et al., 2014). In wet years, late sowing can be recommended; however, year to year yield variability in wet years was relatively large, potentially due to the additive effect of high temperature stress during flowering stages which may induce spikelet sterility thus reduce yield (Peng et al., 2008; Wassmann et al., 2009; Butler and Huybers, 2013) and differences in solar irradiation (Evans and De Datta, 1979; Yang et al., 2008; Deng et al., 2015). We have also demonstrated here that, even with < 100% accurate seasonal forecasts, using the sowing window optimised for dry years potentially resulted in higher productivity than a sowing window informed by average climatological conditions. Selecting sowing dates based on available imperfect and perfect seasonal forecasts resulted in increased yields, thus also farmer revenue. This was found to be more significant for a cropping system using the medium duration rice variety; however, our results also confirm the value in using short duration varieties as an adaptative option when a dry year is forecast, and in drought prone areas as suggested by Atlin et al. (2017) and Radanielson et al. (2019).

We have demonstrated that, even with the current level of accuracy of existing seasonal forecasts (around 70%), the expected economic value for wet season forecasts is at least \$30 ha^{-1} and that this may increase to \$220 ha^{-1}for perfect forecasts in extremely wet years. This assessment framework has demonstrated, for the first time for the study site and the GMR, the value of seasonal forecasts in informing better rice cropping decisions. It also shows that the uncertainty associated with less than perfect (i.e. < 100% accurate or 'imperfect') seasonal forecasts should not limit their use in formulating recommendations for climate sensitive decisions such as suitable sowing windows, particularly when there is a risk of extreme wet or dry conditions compared to the average long term climatic conditions of the region.

Baseline for climate services valuation

The present evaluation provides evidence supporting and reiterating the value of SCFs in supporting climate smart adaptation for farming systems. The developed framework is a robust and objective approach for translating SCFs into actionable solutions for farmers and is expected to be an important practice in enhancing adoption of climates services for decision making in farming systems (Antle et al., 2017). Using the VMD as a case study, we have demonstrated that even imperfect SCFs of extreme conditions may be especially valuable and can be confidently communicated to inform sowing decisions in rice cropping systems.

The present valuation also supports the need for targeted climate services in rice growing countries that are vulnerable to climate variability and climate change impacts. It has the advantage of providing a reference baseline that is often lacking in climate services impact studies (Tall et al., 2018). Long-term data sets of weather and crop yield used here provide a valuable baseline for the evaluation of SCFs and the impact of changes in decision making (i.e. adaptation). Applying this framework in other rice growing areas that are vulnerable to climate variability (e.g. the greater Mekong delta and across Asia and Africa) would be very beneficial in facilitating the communication of climate information to farmers and supporting initiatives in climate adaptation, particularly where there are large uncertainties associated with climate forecasts (Tall et al., 2018). However, the framework relies heavily on data intensive approaches such as modelling and long-term climate data analysis that may be not always available in developing countries where food and nutrition security is most vulnerable to climatic risk. While modelling studies, including calibrated model parameters, are available for most rice growing areas (Gaydon et al., 2017; Li et al., 2017), long term weather data are often less accessible. While case studies such as this are needed to establish the baseline information required to effectively communicate the value of climate information and enhance climate variability and climate change adaptation for more sustainable and resilient agri-food systems, the present valuation can also support decisions at government level to invest in improved regional and national weather station observation networks as well as research, development and extension programs. In addition, improvements in the skill of seasonal forecasts are still needed to increase forecast quality and thus achieve better economic and societal benefits of the forecasts locally and globally.

Improved climate information for upscaling

Increased climatic variability and associated challenges to rice production system in the Greater Mekong Region of Vietnam, and to

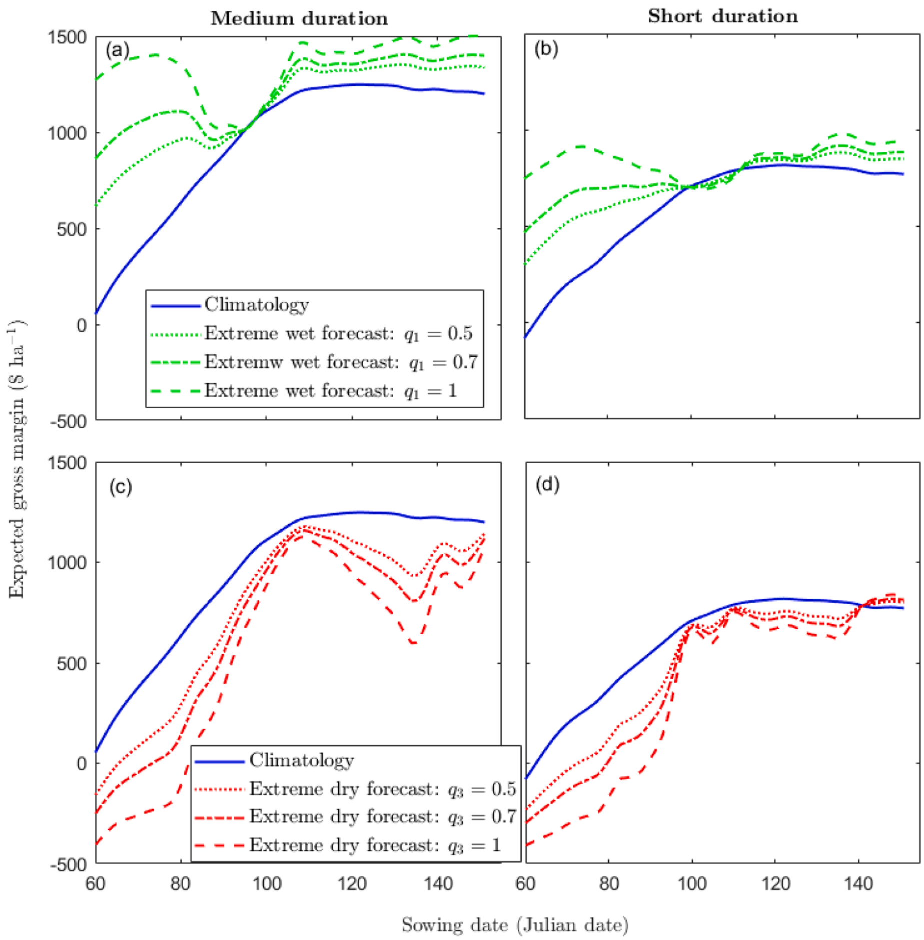

Fig. 6. Expected gross margins for different sowing dates for medium growth duration (Jasmine, left) and short growth duration (OM 5451, right) rice varieties for extreme wet (a & b, respectively) and extreme dry (c & d, respectively) forecasts at three levels of forecast quality (i.e. skill). Climatological results (continuous lines) are presented for reference. For both the varieties, gross margins of imperfect and perfect extreme wet forecasts are relatively diminished when the sowing dates range from Julian date 80 (end March) to 100 (early April) as the risk period of dry spells occurring after 15 days of sowing were the highest among the wet years. The dry spell risk period also falls within the period of increasing high temperature stress factor and a reduced total seasonal radiation as the season progresses (see Fig. S2), reducing potential yields.

agricultural systems globally, highlight the need for improved climate services. While climate information services are widespread, a number of factors are often cited as limiting the uptake and use of seasonal climate forecasts (Hewitt et al., 2020), including current levels of forecast reliability, the need for targeted 'fit for purpose' forecasts, and farmers' perceptions and confidence (An-Vo et al., 2019a). In addition, Pope et al. (2019) have highlighted the need to more clearly establish the benefits and limitations of climate forecasts. Indeed, perceptions of forecast uncertainty are often identified as an impediment to the use of climate information, especially where users find probability forecasts hard to understand and therefore apply in their decision making. According to Kusunose and Mahmood (2016), unless forecast uncertainty is explicitly and realistically incorporated into forecast use frameworks such as the one developed in the present work, and limitations explained, the gap between expected use of forecast information and actual adoption will likely continue. Our findings show that guidelines for sowing dates can be formulated using SCFs. Although the benefit and value of SCFs within climate services, established in the present study, is site-specific, the framework can be easily scaled for different sites and systems, as well as other climate adaptation management strategies such crop variety selection (Haefele et al., 2016).

While farmers and advisers argue the need to improve seasonal climate forecasts (An-Vo et al., 2019a), it is obvious from this study that there is already significant unrealised potential in presently available climate information and climate services in general, which, properly interpreted, offers considerable economic value. Using the example of a climate-sensitive sowing decision related to the rice sowing window, this study shows how climate information, though imperfect, may be of significant potential value in helping rice farmers develop better strategies to improve their productivity and profitability and build resilience in the face of increasing climate variability. It also demonstrates the importance of increasing the skill of seasonal climate forecasts, allowing farmers to make better decisions, with confidence, to manage climate risk and enhance production. With higher resolution of SCFs, this framework can provide farm specific valuation for farmers, increasing its usefulness for adaptation strategies on farms. Though the skill of SCFs has significantly increased during the last decade, further research is still required to improve downscaling approaches for SCFs at farm level (Hayashi et al., 2018). Similarly, further investment to establish the data environment for regional and local application is needed to scale the present approach to a range of climate services. There is, therefore, a key challenge for the global climate centers to continue to improve the skill of climate forecasts at a range of scales and to improve communication and thereby the capacity of decision makers such as farmers for improved decision making (Hewitt et al., 2021).

Limitations

The recommended optimal sowing date based on imperfect seasonal precipitation forecast achieved in the present work is in an expected economic sense rather than event-based. We acknowledge that the recommended sowing date migh be sub-optimal for some specific seasons. For example, some wet seasons may have a lot of rain early on with premature cessation of the monsoon; some dry seasons may have a delayed onset. In such dry seasons, the crop may not receive enough water in the critical early development stages to thrive if sown too early. Likewise, if sown too late in such wet seasons, the crop may not be able to benefit from the early season rains and may still be exposed to heat stress and excess evapotranspiration at the end of the season. These seasonal situations confirm the importance of being able to predict the

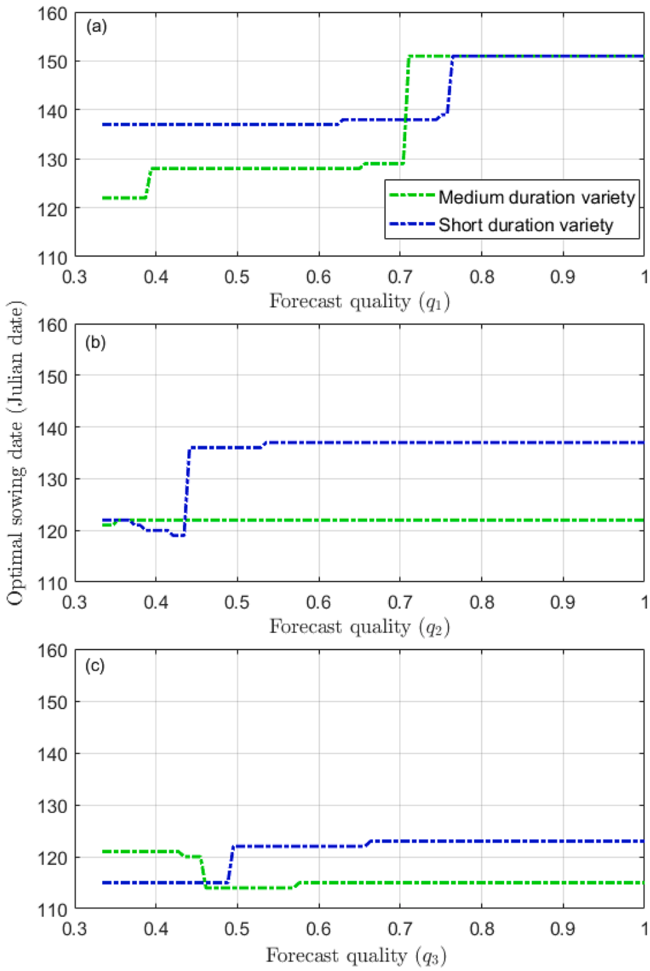

Fig. 7. Optimal sowing dates indicated by seasonal precipitation forecasts of moderate conditions for medium growth duration (Jasmine) and short growth duration (OM 5451) rice varieties as a function of forecast quality (ranging from uninformed (33%) to perfect (100%) skill) for (a) moderate wet, (b) normal and (c) moderate dry forecasts.

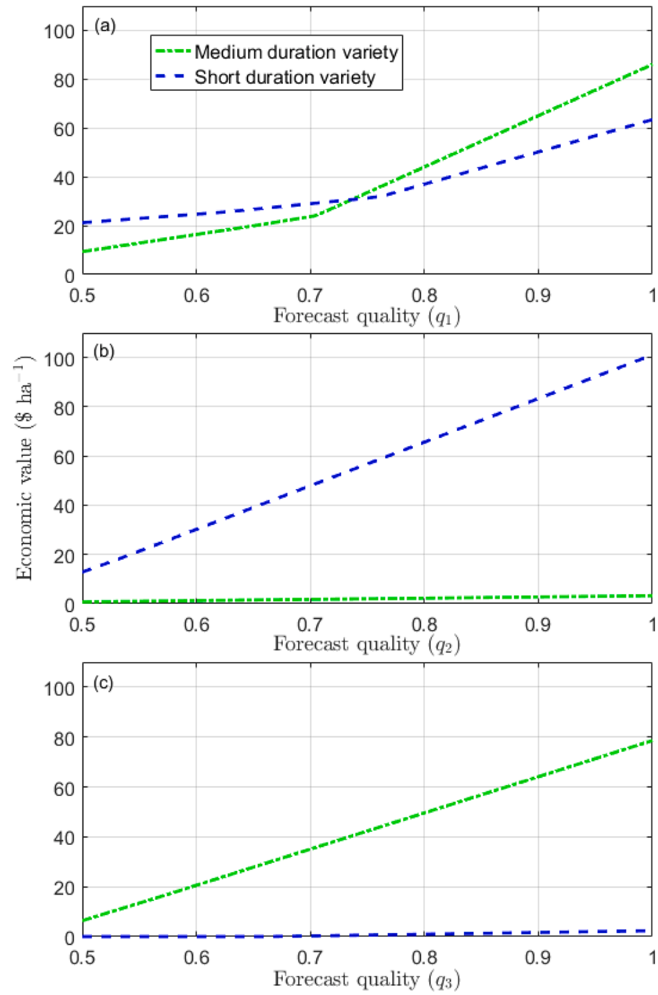

Fig. 8. Economic values of seasonal precipitation forecasts of moderate conditions for medium (Jasmine) and short (OM 5451) growth duration rice varieties by forecast quality for (a) moderate wet, (b) normal; and (c) moderate dry forecasts.

onset of the wet season as well as the total cumulative rainfall over a growing season, both of which are key factors in rain-fed rice cropping systems (Lacombe et al., 2012). However, the recommended sowing date achieved in the present work would be optimal in long-term average sense for the studied seasonal precipitation forecasts.

The results of this study indicate that skilful seasonal climate forecasts can potentially assist farmers in making seasonal climate sensitive decisions such as sowing date selection. However, it should be noted that this study has investigated just two rice varieties at one location and that outcomes may be sensitive to differences in location, soil type and pricing structure (Hammer et al., 1996); hence, further work is required to investigate the applicability of these findings in other locations and rice cropping systems. In the present study, we have only considered crop variety duration in the valuation of seasonal forecast in supporting sowing decision in wet season cropping. We have shown that use of a medium duration rice variety (e.g. Jasmine) might achieve higher returns when sown at the adaptive sowing date in dry and wet years compared to shorter duration varieties (e.g. OM5451) often used in wet season rice production systems. This finding suggests that the general recommendation for use of short duration varieties in climate smart cropping can be improved, particularly for seasons for which extreme conditions are forecast, with a combination of information about optimum sowing dates and variety choice for maximum profitability. Additional consideration of varieties with characteristics such as tolerance to drought, flash flood and waterlogging were not included in the present study due to limitations in the ability of the crop model to represent these stresses and the availability of data to quantify the level of tolerance of and difference between varieties. These factors are important determinants of the productivity of rainfed rice systems and are certainly relevant for further investigation. We have also explored the value of seasonal climate (precipitation) forecast information for just one decision, the sowing date. Farming involves multiple decisions, all of which may influence yield and profitability, and further study is needed to explore value in a more integrated decision-making context.

The potential benefit of using SCFs in rice crop sowing date selection was estimated for the case study site and is indicative only. Estimates of absolute values using the framework at farm level have limitations due to uncertainties associated to the source of data used to inform the model, as well as the ability of the model to account for spatial variability within the rice field. Simulations of crop yield using gridded weather data are also uncertain. In all instances, we have tried to reduce these uncertainties by using a well calibrated and validated model, rainfall data from the local weather station and gridded weather data including solar radiation and temperature from the NASA-POWER database, which has reportedly good agreement with local station data (Van Wart et al., 2013). Further application of the valuation framework presented here will benefit from access to local specific weather data and by leveraging existing modelling studies in addition to up to date

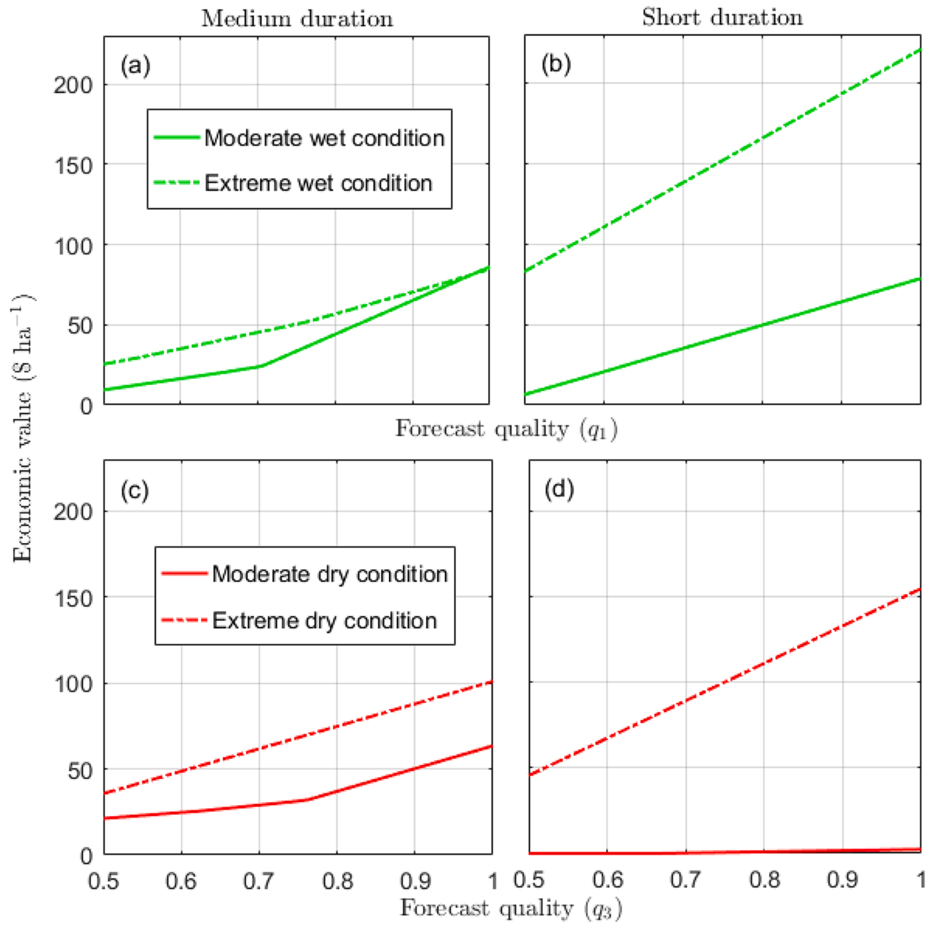

Fig. 9. Economic values of extreme wet and extreme dry forecasts as functions of forecast quality for crop using medium growth duration (Jasmine, left column) and short growth duration (OM 5451, right column) rice varieties. Forecast values for moderate conditions (continuous lines) are provided for comparison.

cropping systems surveys and monitoring. Improved downscaling and increased skill of seasonal forecasts will also help to reduce these uncertainties for farm scale and site-specific applications.

Conclusion

Economic valuation of climate services provides an improved tool to communicate and translate climate knowledge, by facilitating its dissemination and adoption, into actionable solutions to reduce climate risk. We analysed seasonal precipitation and associated rice crop yield responses to demonstrate the significance of seasonal rainfall variability and its impacts on rice crop production in the Vietnamese Mekong Delta, representative of the climatic conditions in the Greater Mekong Region. We examined rice crop yield variability in relation to the current sowing window of the early wet season, a critical period of regional climate variability, and the decision on when to sow the crop to achieve optimal benefits. We developed an end-to-end (integrated) seasonal forecasting framework to demonstrate the usefulness, and to quantify the economic values, of seasonal precipitation forecasts of moderate and extreme conditions. This is the first time such climate information has been developed and its value demonstrated for rice crop production in the region.

Seasonal rainfall variability was found to be significant with large impacts on rice production (up to 3 t ha^{-1}) and profit (up to $1000 ha^{-1}) in the case study site. Our results indicate that the value of seasonal precipitation forecasts when making sowing decisions may be up to $220 ha^{-1}. A better and narrower sowing window can be recommended for the case study site and potentially for the region, with significant potential yield benefits. We demonstrated that seasonal precipitation forecasts provide useful information for rice farmers in selecting the best sowing date. The developed seasonal forecasting framework, however, is general – able to be applied to other climate sensitive decisions in crop production provided validated crop models. If a validated crop model is not available, the framework can also be employed with recorded data of yields and profits for decision making at farm. Application of the present approach for different climate services will facilitate communication and enhance adoption of climate services by farmers and larger communities that are increasingly vulnerable to climate risk. We thus anticipate that the seasonal forecasting framework developed in this work has potential to improve the value and adoption of climate services for rice production not only in the Great Mekong Region but for rainfed rice growing areas globally and agricultural production systems more broadly.

Declaration of Competing Interest

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

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Authorship

All authors participated in the conceptualisation and development of the manuscript throughout. AR conducted the crop modelling; D-A A-V developed the decision analytic framework and built the integrated bioeconomic models and ran the analyses; AR and D-A A-V wrote the draft manuscript; and KR-S, SM and CH provided feedback on the analysis and interpretation, as well as contributions to the final manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cliser.2021.100234.

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