Rice Cultivation and Harvest Date Identification Based on a Hidden Markov Model

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***Abstract*—Rice cultivation and harvest dates are very useful information since they are the key factors in rice monitoring, yield estimation and damage assessment. This paper proposes a new approach to estimate rice cultivation and harvest dates by using the 8-day composite normalized difference vegetation index (NDVI) derived from Moderate Resolution Imaging Spectroradiometer (MODIS) data. However, the NDVI time-series data suffered from cloud contamination. Using the filter to reconstruct to the cloud-free NDVI data can introduce the artifact that may result in incorrect estimation of cultivation harvest dates. As a result, we employ the hidden Markov models to characterize the rice growth states and atmospheric conditions. Here, we divide the rice growth states into 4 states, nothing, growing, mature, and harvest in which two atmospheric conditions, namely, the clear and cloudy skies can occur. The optimum growth states and atmospheric conditions are determined using the Viterbi algorithm. In the experiment, we compared with the ground truth data with the estimated cultivation and harvest dates, and found the average errors for cultivation dates and harvest dates of the rain-fed rice 16.128 days and 8.734 days, respectively. For the irrigated rice, the errors are 17.524 days and 12.516 days for cultivation and harvest dates, respectively.**

Keywords—*MODIS; NDVI; Hidden Markov Model; Viterbi Algorithm*

I. INTRODUCTION

In 2011, Thailand faced its worst flooding in half a century, leaving severe impairments to the country's economy, industrial sector, and society. The flood inundated 90 billion square kilometers of land, more than two-thirds of the country. Ten thousand square kilometers of damaged areas are rice field. To ease the financial burden to Thai farmers, Thai government issued a policy to subsidize the damaged rice fields depending on the development stage of the rice. In order to accurately estimate the growth of the rice, the key factor is the cultivation date and harvest date of the rice. Since the rice cultivation areas are expanses, ground surveys would require huge resources.

The satellite image such as the moderate resolution imaging spectroradiometer (MODIS) has been widely used to obtain crop phenology information in many works [1]-[9]. One MODIS product is the normalized difference vegetation index (NDVI) which can indicate the vegetation density and conditions. The NDVI time-series data are widely used in vegetative studies.

The rice cultivation date estimation has been proposed in some studies [1],[2],[8]. The study by Suwannachatkul et al. [1] focus on the rain-fed and divided the rice growth state into 4 state, nothing, growing, mature, and harvest. Then they applied these state of the rain-fed rice into Hidden Markov Model (HMMs) and used Viterbi algorithm to define the rice state in MODIS NDVI time-series data. They used these defined state the estimate the cultivation and harvest date. The problem in this study is the data applied to their model is required a continuous and smooth NDVI curve. However, Thailand is commonly known that there are a lot of cloud contaminations in satellite images. The Savitzgy-Golay filter they used cannot handle some continously the noise in NDVI time-series data and cause some error in date estimation.

The study by Chumkesornkulkit et al. [2] proposed to model the MODIS NDVI data as a triply modulated cosine function to identify the cultivation date estimation on rain-fed and irrigated rice. Then, they used the extended Kalman filter (EKF) to smooth the data and estimate the parameters of the cosine function. The reported that 75.56% of the estimated cultivation dates of rain-fed rice are with 16 days of the actual dates whereas 83.33% the estimated cultivation dates for irrigated rice are within 16 days.

Sakamoto et al. [8] used the MODIS Enhanced Vegetation Index (EVI) smoothed by wavelet operation to detect the rice phenology. They estimate the cultivation date by identify the heading date (peak of the NDVI curve), the minimal point (the first derivative equals 0 and changes from negative to positive at this point), and inflection point (the second derivative equals 0 and changes from negative to positive at this point). The minimal point and the inflection point are only the point that earlier than 60 days from the heading date. The later one of these two points was automatically taken as the estimated cultivation date. However, by fixing the estimate date in between 60 days from the heading date made the algorithm isn't flexible. The heading date can also be effect by the noise and can cause the estimation errors. Especially, the noisy NDVI data in Thailand can cause a lot of these errors.

Another crop phenology date estimation by Zhao et al. [5] used the MODIS NDVI time-series data to estimate the phenology date of the corn and soybean in State of Iowa, USA. The Savitzky-Golay filter have been used to smooth the NDVI time-series data and compared them with a method using a double logistic function. After that, they used the derivatives of the smoothed data to detect the vegetative to reproductive period, the emerged dates and harvest dates using their own defined characteristics.

There are few study applied the Hidden Markov Model (HMMs) with the NDVI time-series data. The study by Shen et al. [7] uses their modelled HMMs to estimate corn progress percents in state of Iowa, USA. Three different time-series data, fractal dimension (FD), mean NDVI, and Accumulated Growing Degree Days (AGDDs), are used in their modified HMMs to access the corn progress in the area.

Even though most of the studies encountered a problem with the data qualities which were affected by cloud contamination and atmospheric variability, most of the studies solve this problem by using filter [1]-[6] or wavelet operation [8],[9] to reconstruct the smoother time-series data. This method may be suitable for low cloud areas. However, this method may not perform well in the high cloud contaminated areas such Thailand. The distortion by cloud contamination causes the NDVI data drop drastically since cloud reflect both red and near-infrared spectrums in the similar level. However, this sharp drop of the NDVI can be caused from other factors such the harvest. Hence, the smooth NDVI data in high cloud coverage areas such as Thailand might cause some changes to be smooth out. As a result, the estimate of cultivation and harvest dates in these smooth data can be very poor. For example, in Fig.1, the red dot shows the rice cultivation date estimate by the expert using the smooth data by Savitzky-Golay filter [6] and the black dot shows the actual cultivation date. The date estimation error is 9 samples which is 27 days. The estimation errors is quite high because of the rapid change of the NDVI data which have characteristics same as noises and cause the filter to reconstruct these data.

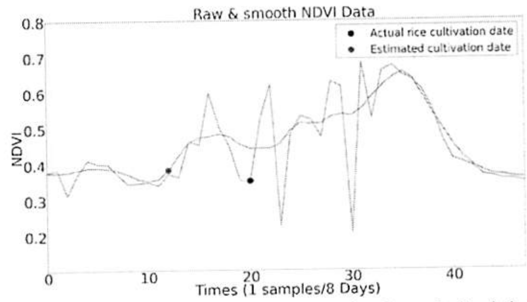

Fig.1 Raw and smooth NDVI time-series data of rain-fed rice in 2004 from Khonkean province. The red line is the smooth data and the green line is raw data.

The purpose of this study is to improve the algorithm proposed in Suwannachatkul et al.[1] by using the raw NDVI time-series data to estimate the rain-fed and irrigated rice cultivation and harvest date. By following the work by Suwannachatkul et al.[1], we define the ideal NDVI time-series data of rice in a cultivation period to be divided into 4 stages (nothing, growing, mature, harvest) with adding two atmospheric conditions (cloudy and clear skies) to handle the cloud contamination data. Then, the Viterbi algorithm is then applied to find the optimum growth states and atmospheric condition on the raw NDVI data. After obtaining the rice growth state, the cultivation and harvest dates are then carried out.

II. DATA AND PRE-PROCESSING

A. Study Area

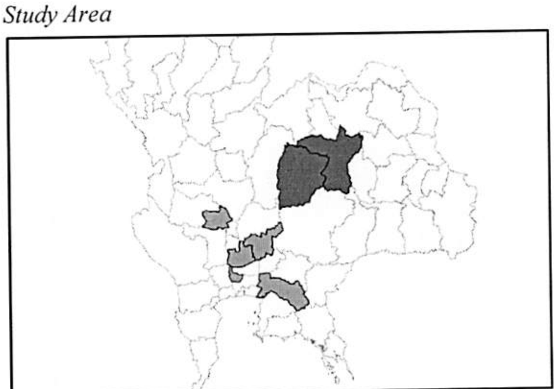

Fig.2 The 7 study areas, Ayutthaya, Chachoengsao, Nonthaburi, Saraburi, Chainat, Khonkean and Chaiyaphum provinces, Thailand. Red and green label shows the provinces that mainly growing rain-fed rice and irrigated rice, respectively.

As shown in Fig.2, the data collected around Khonkean and Chaiyaphum provinces are used in this experiment for rain-fed rice. These two provinces are located in Northeastern region of Thailand which is the rice major production area. Most of the rice cultivated in these areas is rain-fed rice which is high quality rice and can be grow only one crop per year. The rice in these areas is planted during the rainy season and takes about six months before ready to harvest. The other five provinces located in central region of Thailand are Ayutthaya, Chachoengsao, Nonthaburi, Saraburi, and Chainat provinces. These provinces are known to cultivate irrigated rice which can be cultivated many times in a year with period about four months. In this study, we only experiment with the irrigated rice that cultivated 2 crops per year. Due to, the 8-day composite data in this study is too coarse to detect the rapidly changing of the NDVI time-series data for the rice that cultivated more than 2 crop per year [2].

B. Ground truth data

This ground truth data provided by Thailand's rice department consist of location information (UTM coordinates and province), cultivation and harvest dates of rice. The obtained data provide rice information which consists of 45 and 40 areas which have cultivation date and harvest dates of rain-fed rice and another 25 areas for cultivation and harvest date of irrigated rice. This data will be used to access the accuracy of the date estimation by our algorithm.

C. MODIS Data

The 8-day MODIS/Terra composite data (MOD09Q1) acquired from NASA from 2000 to 2012 are used as the experiment data. This image data have 250meter resolution, and can be obtained every 8 day in the red and near infrared (NIR) spectral bands (0.6µm - 0.9µm). This data can also download freely via the Earth Observing Data Gateway. The data were re-projected to the Geographic coordinate over Thailand. The NDVI time-series data is derived from red and NIR bands of MOD09Q1 datasets as (1).

$$NDVI = \frac{NIR-RED}{NIR+RED} \qquad (1)$$

III. METHODOLOGY

A. Method description

Because of the simple characteristics NDVI of the rice, we declare the ideal NDVI profile of rain-fed rice and irrigated rice in a year as shown in Fig. 3 which includes the nothing state where NDVI value is the value of bare soils (≈0.3), the growing state where NDVI value is increasing, the mature state where NDVI is saturation, and the harvest state where NDVI value is decreasing.

Let x_k be the state of rice at the k-th sample (Fig. 3(a) and Fig. 3(b)) It is clear that the possible states of x_k are nothing, growing, mature and harvest which are denoted as n, g, m, and h, respectively. Furthermore let $P_{i \to j}$ be the transition probability from the state i to the state j. In this paper, we assume that the rice states can only change from nothing to growing, growing to mature, mature to harvest, and harvest to nothing. Fig.4 depicts the state transition considered in this paper. In each state, there are two possible atmospheric conditions, namely, cloudy and clear skies. In the cloudy sky, the NVDI is lower than those in the clear sky due to cloud contamination in a pixel. We assume that the atmospheric conditions of cloudy and clear also follow another hidden Markov model as shown in Fig. 5. As a result, there are the total of 8 states, nothing and cloudy sky, nothing and clear sky, growing and cloudy sky, growing and clear sky, mature and cloudy sky, mature and clear sky, harvest and cloudy sky and harvest and clear sky.

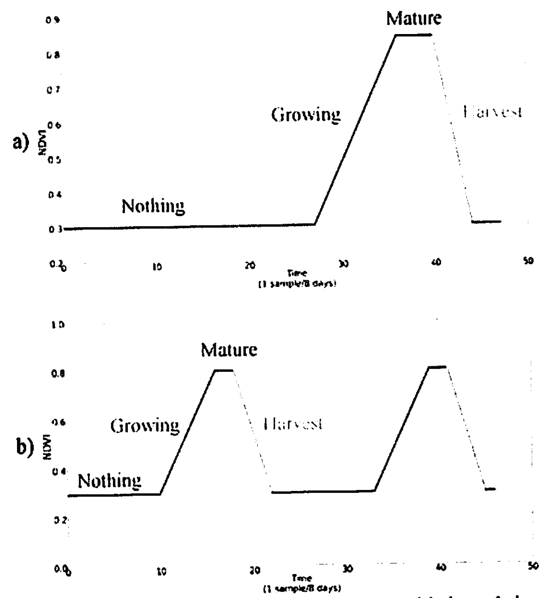

Fig.3 Ideal NDVI profile of rain-fed rice (a) and irrigated rice (b) in a year and its states

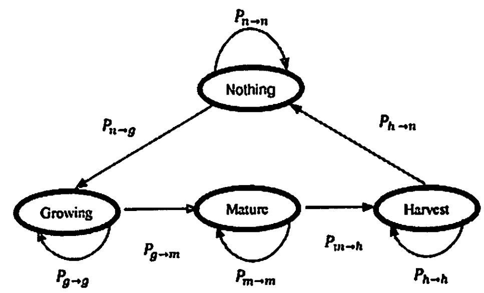

Fig.4 Hidden Markov Model of 4 states in NDVI data

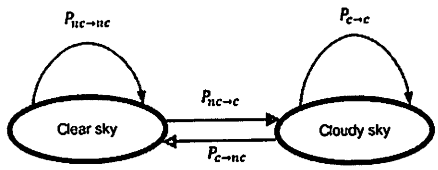

Fig.5 Hidden Markov Model for state with cloud and without cloud for state nothing, growing, mature and harvest.

TABLE I. THE TRANSITION PROBABILITY OF THE RAIN-FED RICE

Transition probability	Value of transition probability
$P_{n\to n}$	27.55/28.55
$P_{n\to g}$	1/28.55
$P_{g\to g}$	8.1/9.1
$P_{g\to m}$	1/9.1
$P_{m\to m}$	1.7/2.7
$P_{m\to h}$	1/2.7
$P_{h\to h}$	4.85/5.85
$P_{h\to n}$	1/5.85

Next, we estimate the transition probabilities from the actual observed NDVI data from 20 different samples, and found that, on average, the length of nothing, growing, mature, and harvest states in a year (356/8 ≈ 46 samples) for rain-fed rice (one crop per year) are 28.55, 9.1, 2.7, and 5.85 samples, respectively. Since the average number of samples that rice remains in a given state i is equal to$1+\frac{P_{i\to i}}{1-P_{i\to i}}$, the transition probabilities are given in Table I.

TABLE II. THE TRANSITION PROBABILITY OF THE IRRIGATED RICE

Transition probability	Value of transition probability
$P_{n\to n}$	17.75/18.75
$P_{n\to g}$	1/18.75
$P_{g\to g}$	11.05/12.05
$P_{g\to m}$	1/12.05
$P_{m\to m}$	4.3/5.3
$P_{m\to h}$	1/5.3
$P_{h\to h}$	10.25/11.25
$P_{h\to n}$	1/11.25

For irrigated rice (2 crop per year), the average length of nothing, growing, mature and harvest state are18.75, 12.05, 5.3, 11.25, respectively. Similar with the rain-fed rice, the transition probabilities of irrigated rice are shown in Table II.

TABLE III. THE TRANSITION PROBABILITY OF THE ATMOSPHERIC CONDITIONS OF CLOUDY AND CLEAR SKIES

Transition probability	Value of transition probability
$P_{c\to c}$	2.25/3.25
$P_{c\to nc}$	1/3.25
$P_{nc\to nc}$	9.45/10.45
$P_{nc\to c}$	1/10.45

For transition probability of the atmospheric conditions of cloudy and clear skies, we follow the same procedure as for rice cultivation states and found that, on average, the cloudy and clear skies contains for 3.25 and 10.45 consecutive samples, respectively. The transition probabilities are shown in Table III.

In this paper, for a given pixel s_k, we assume that observed NDVI is a function of the cloud-free NDVI value, Z_k, the portion of cloud-contamination, the NDVI value of pure cloudy pixel, and a measurement noise, i.e,.

$$Y_k = \gamma_k Z_k + (1-\gamma_k)C + N_k \tag{2}$$

where Y is an observed NDVI value, γ_k is the portion of cloud in s_k, C is the NDVI value of a pure cloudy pixel, and N_k is a measurement noise. Since cloud reflects the red and near-infrared spectrums similarly, the NDVI value of a pure cloud pixel is assumed to be zero. Furthermore, if a pixel is cloud-contaminated, the portion of cloud in this pixel is assumed to be uniformly distributed between zero and one. Hence, $\gamma_k Z_k$ is uniformly distributed between zero and Z_k. Next, we assume further that N_k has Gaussian distribution with zero mean and variance of σ_n^2. Hence, the probability density function (PDF) of z_k can be written as

$$f_{Y_k}(y_k) = f_{\gamma_k Z_k}(\gamma_k z_k) * f_{N_k}(n_k)$$
$$= \int_{Y_k - Z_k}^{Y_k} \frac{e^{-\frac{\lambda^2}{2\sigma_n^2}}}{Y_k\sqrt{2\pi\sigma_n^2}} d\lambda \tag{3}$$

By using the definition of error function where $\mathrm{erf}(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}dt$, Eq. (3) can be rewritten as

$$f_{Y_k}(y_k) = \frac{1}{2Y_k}\left[\mathrm{erf}\left(\frac{Y_k}{\sqrt{2}\sigma_n}\right) - \mathrm{erf}\left(\frac{Y_k - Z_k}{\sqrt{2}\sigma_n}\right)\right] \tag{4}$$

Next, the NDVI value in the nothing, growing, mature and harvest stages are denoted by μ_n, μ_g, μ_m and μ_h, respectively. Since, in the nothing state, most of ground cover is bare soil or light vegetation, the value of μ_n is assumed to be a constant. In the growing state, the area covered by rice leaf increases from one sample to another. Hence, we assume that $\mu_g = \mu_n + \alpha g_k$ where g_k is the number of samples in the growing state, and α is the incremental rate of the NDVI value. When the rice reaches the mature state, the NDVI value is saturated and constant. Lastly, during the harvest, the NDVI value drops sharply. As a result, we assume $\mu_h = \mu_m - \beta h_k$ where h_k is the number of samples in the harvest state, and β is the rate of decrease of the NDVI value.

In this work, the unknown parameters $(\alpha, \beta, \mu_n, \mu_m, \sigma_n^2)$ are estimated by using some selective sample data in each provinces and each type of the rice.

B. *Optimum solution*

To determine the rice growth state, we employ the maximum *a posteriori* (MAP) criteria, i.e.,

$$X_{1:N}{}^{opt} = \arg\max_{X_{1:N}} \Pr(X_{1:N}|Y_{1:N}) \tag{5}$$

where $X_{1:N} = \{x_1, \dots, x_N\}$ and $Y_{1:N} = \{Y_1, \dots, Y_N\}$. By using the Bayes' rule, and the fact that Pr $(Y_{1:N})$ is independent of the choice of $X_{1:N}$, Eq. (5) can be modified to

$$X_{1:N}{}^{opt} = \arg\max_{X_{1:N}}[\Pr(Y_{1:N}|X_{1:N})\Pr(X_{1:N})]. \tag{6}$$

Furthermore, we assume that the observed NDVI from any distinct samples are statistically independent when X_N are given, and depends only on the previous and current state of rice. By applying the chain rule, the MAP criteria becomes

$$X_{1:N}{}^{opt} = \arg\max_{X_{1:N}} \left[P(x_1) \prod_{k=1}^{N} \Pr(Y_k|X_{1:k}) \Pr(x_k|X_{1:k-1}) \right]. \quad (7)$$

Since log(.) is monotonically increasing function, Eq. (7) can be rewritten as

$$X_{1:N}{}^{opt} = \arg\min_{X_{1:N}} \left[\sum_{k} E_k(Y_k, X_{1:k}) \right] \quad (8)$$

where

$$E_k(Y_k, X_{1:k}) = -\begin{cases} \log \Pr(x_1) + \log \Pr(Y_1|x_1) & k = 1 \\ \log \Pr(x_k|X_{1:k-1}) + \log \Pr(Y_k|X_{1:k}) & k \neq 1. \end{cases} \quad (9)$$

To find the solution of Eq. (8), we used the Viterbi algorithm and create the trellis diagram (Fig.6) that collects all the possible paths of thrice growth in time-series data. Each path has its own weight. The weight of each path is calculated by the sum of the all branches the path passing through. The weight computation depends on the observed NDVI value and the next state. For example, if the NDVI value is about 0.3, the weight of paths that are in state nothing will be low and the weight of paths that are in state mature will be high. If a particular node is reached by two or more path the Viterbi algorithm will keep the path with lowest cost and ignore the rest. Then, weight of all final possible paths are compared to find the path that has the lowest weight and use the state that this path go though as the state of NDVI time-series data. In fact, we assign the weight of each path equal to $E_k(Y_k, X_{1:k})$.

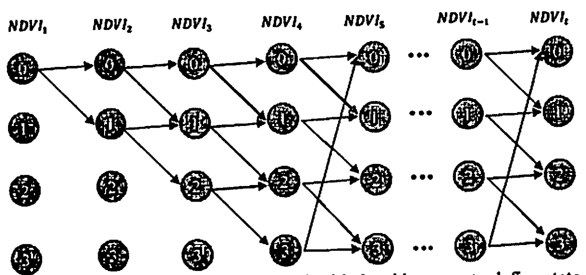

Fig.6 The example trellis diagram of Viterbi algorithm uses to define state of each NDVI value ($NDVI_1, NDVI_2, \ldots, NDVI_t$).
0 = nothing state with and without cloud, 1 = growing state with and without cloud, 2 = mature state with and without cloud, 3 = harvest state with and without cloud

IV. Experimental Results& Discussion

A. Experimental Result

After we apply the proposed algorithm to the NDVI time-series data, the resulting cultivation states of rice are plotted in Fig. 7(a) and 7(b) for particular locations in rain-fed rice from Chaiyaphum province and in irrigated rice from Saraburi province. In these plots, the red, green, blue and yellow colors represent the nothing, growing, mature and harvest states, respectively.

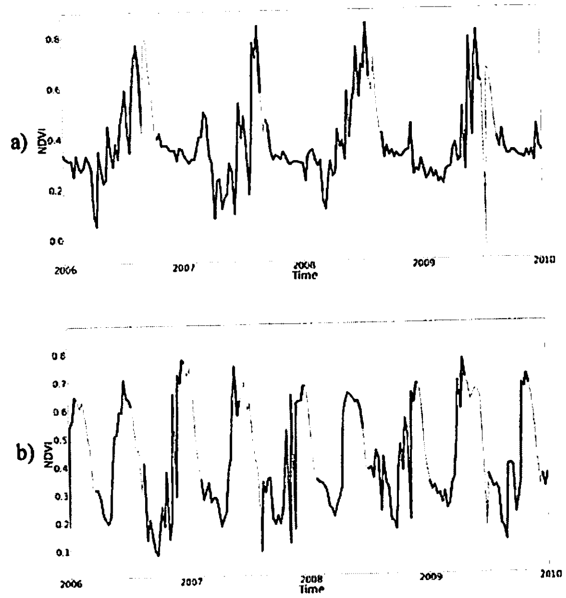

Fig.7 The state defining result of rain-fed rice data from Chaiyaphum province (a) and irrigated rice from Saraburi province (b).The red, green, blue, and yellow lines represent nothing state, growing state, mature state, and harvest state respectively.

In this experiment, we define the cultivation as the last sample of the nothing state before the beginning of growing state. Similarly, we define the harvest date as the last sample of harvest state before moving to the nothing state.

For the accuracy assessment, we used 45 areas of cultivation dates and 40 areas of harvest dates of rain-fed rice and 25 areas of cultivation and harvest dates for irrigated rice comparing with estimation dates from the algorithm. We also compared our proposed algorithm result with the algorithm proposed by Suwannachatkul et al.[1] and Chumkesornkulkit et al.[2] but the algorithm by and Chumkesornkulkit et al.[2] only estimating the rice cultivation date. The results are shown in Table. II. For the rain-fed rice, the average sample error is at 1.891 samples in estimating the cultivation dates and 1.046 samples for the estimate of harvest dates. The corresponding averaged errors in days for rain-fed rice are 14.429 and 10.047 days for cultivation and harvest dates, respectively. The date estimation errors in irrigated rice are 17.772 days or 2.227 samples for cultivation date and 13.941 days or 1.579 samples for harvest date.

TABLE IV. Cultivation & Harvest Date Estimation Error

Algorithm	**Average Cultivation date estimation error (days)**		**Average Harvest date estimation error (days)**	
	Rain-fed rice	***Irrigated rice***	***Rain-fed rice***	***Irrigated rice***
Proposed algorithm	14.429	17.772	10.047	13.941
Suwannachatkul et al.[1]	17.52	18.568	10.73	15.423
Chumkesornkulkit et al.[2]	15.125	16.341	-	-

B. Result Discussion

The cultivation and harvest date estimation by using our algorithm can be used to estimate the cultivation and harvest dates for both rain-fed and irrigated rice fields. The overall accuracy is acceptable even though the 8-day composites data were employed.

The harvest date estimation has more accurate results than the cultivation date due to the fact that the growing season in rain-fed rice usually start in rainy season which have lots of cloud contaminations. This makes the noises of NDVI data in this period occurs continuously. These continuously noises might affect the state defining process. On the other hand, there are very few cloud contaminations in harvest periods. By the reason that the NDVI data in harvesting period are less effect by the noise, the result by our algorithm are proximate to algorithm by Suwannachatkul et al.[1].

Because of the rapid change in NDVI data of irrigated rice, sometimes a large amount of noises could cause the data cannot stay in NDVI curve. This explain the reason that the algorithm by Chumkesornkulkit et al.[2] have better result in irrigated rice. The extended Kalman filter used in their works tend to reconstruct the noisy data into the cosine curve which help recovery the lost data.

The other factor that can cause the errors in date estimation process is the unexpected farming of farmer. In some areas, the farmers usually use their fields for growing other plant before growing the rice. When the farmers are ready to plant their rice, they just promptly clear their field for the rice in few days. This will cause the NDVI data increasing for a period of time and then quickly drop back to the NDVI value of the bare soils. After that, the NDVI start to increase again when they start growing the rice. This event can affect the state defining process.

V. CONCLUSION

In this study, we proposed a new approach to identify the rice cultivation and harvest dates using the raw NDVI time-series data by dividing the rice's NDVI time-series data into 4 states (nothing, growing, mature, harvest) with two atmospheric conditions, namely, cloudy and clear skies. We use the hidden Markov model to define state transition and its probability. After that, we use Viterbi algorithm for applying the state into the NDVI time-series data. Then, we find the rice cultivation and harvest date by using these defined state. The cultivation and harvest date estimation result have acceptable accuracy. The average error of harvest date estimation is less than 8 days or less than two samples. In cultivation date estimation, the accuracy drops because of noise effect from cloud in growing season and unexpected farming of farmer but the result still has average error around 14 days for rain-fed rice and 17.7 days from irrigated rice which are still satisfactory accuracy. Apart from the rice cultivation and harvest date estimation, the result in this study also has the state of the rice in the NDVI time-series data which can be useful in future study.

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