Relationship Between Severe *El Niño* Phenomena and Malaysia's Palm Oil Production – A VECM Approach

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ABSTRACT

The palm oil sector has faced various challenges throughout the past decade. Climate variability is one of the major challenges to the Malaysian oil palm industry. In order to achieve higher production, oil palm needs an average maximum temperature of 29°C-33°C and an average minimum temperature of 22°C-24°C. Variability in climate leading to the development of El Niño and La Niña events, thus, affects the production of palm oil. This study focuses only on the prolonged dry and hot weather phenomenon known as El Niño. So, the following question was considered: What is the relationship between the El Niño phenomenon and Malaysia's palm oil production? Variations in crude palm oil (CPO) production, fresh fruit bunch (FFB) yield and Ocean Niño Index (ONI) from January 2007 to December 2016 (n= 120) were analysed, based on a multivariate co-integration approach called the Vector Error Correction Model (VECM). The study found that in a long run, FFB yield and ONI influenced total palm oil production. A significant error correction term (ECT) and negative coefficient value (-0.233) show that an adjustment is needed in a short-run disequilibrium towards achieving a long-run equilibrium. The higher the value, the quicker is the adjustment needed towards a long-run equilibrium. The value of ECT showed that an adjustment of 23.3% is needed each month towards achieving a long-run equilibrium. It can be concluded that in order to gain higher CPO production, a longer time is needed because it is influenced by FFB yield and ONI. Hence, the results from this study will be able to help policymakers be aware that owing to extreme weather and its implications on palm oil production. A better irrigation system or in-depth R&D on the advance technologies need to be implemented to offset the negative effects of this phenomenon.

Keywords: *El Niño*, CPO production, FFB yield, Ocean Nino Index (ONI), error correction term (ECT).

INTRODUCTION

El Niño events are associated with warming of the central and eastern tropical waters of the Pacific Ocean, while *La Niña* events are the reverse, with sustained cooling of these same areas. These changes in the Pacific Ocean and its overlying atmosphere occur in a cycle known as the *El Niño*–Southern Oscillation (ENSO). *El Niño* and *La Niña* episodes typically last from nine to 12 months, but some events may be prolonged to last for years. While their frequency can be quite irregular, *El Niño* and *La Niña* events occur, on average, every two to seven years. Typically, *El Niño* occurs more frequently than *La Niña*.

The *El Niño* weather effect occurs when the Ocean Niño Index (ONI) rises above 0.5 for five consecutive months. ONI is the standard for measuring deviations from normal temperatures. A strong *El Niño* effect will cause hot and dry conditions especially in Southeast Asian countries, although it may not immediately impact on palm oil production. Indonesia, Malaysia and Thailand are the three largest palm oil-producing countries in Southeast Asia, together accounting for 90% of the world's production.

Climate variability affects many human activities, including agriculture. On an inter-annual scale, ENSO events produce extreme oscillations in climatic variability of the tropical regions, and these oscillations have great socioeconomic impact. ENSO events have caused millions of dollars in economic losses, especially in the agriculture sector.

Growing global demand for palm oil in the last decade has resulted in a tremendous increase in the total area of oil palm cultivation. In Malaysia, *El Niño* is expected to occur between June and August, and most likely ends by the following year, although this is more prominent in Sabah, the northern part of Sarawak and the eastern part of Peninsular Malaysia. However, the strength of the *El Niño* effect is not known beforehand.

The climate of Peninsular Malaysia can be ascribed to four seasons, namely two monsoon seasons and two inter-monsoon seasons. The Southwest Monsoon season occurs from May to September while the Northeast Monsoon season occurs from November to March. The Southwest Monsoon is drier, particularly for the west coast of the peninsula while the Northeast Monsoon brings heavy rainfall, mainly to the east coast states of Peninsular Malaysia, western Sarawak and the northeast coast of Sabah. The transition periods between the monsoons are known as the inter-monsoon seasons, which often result in heavy rainfall, usually occurring in the form of convective rains. During the inter-monsoon seasons, the west coast of Peninsular Malaysia is generally wetter than the east coast.

According to Brunner (2002), ENSO is economically important and has shown statistically significant effects on the world's real commodity prices. A one standard-deviation positive surprise in ENSO will cause an inflation in real commodity price of about 3.5%-4%. Moreover, ENSO appears to have accounted for almost 20% of the commodity price inflation movements over the past several years.

A strong *El Niño* weather pattern reduced rainfall during 2015 and early 2016, causing a drought which affected the yields of both food and plantation crops in most countries in the region affected by *El Niño*. Rainfall in Malaysia's prime oil palm areas in both the eastern and western parts of the country fell below the expected ranges of time, resulting in a prolonged period of moderate drought stress. January and March of 2016 showed the lowest soil moisture but were quickly followed by near-normal rainfall between May and July as the *El Niño* phenomenon began to weaken. Despite the subsequent improvements in precipitation, the damage had already been done to the oil palm crop.

Oil palm is a rain-fed crop in Malaysia and its yield can be influenced by any severe change in rainfall intensity and/or its distribution. Some important environmental stresses such as drought or extreme rainfall can have great impacts on crop productivity. The intensity of impact will depend on the severity, duration and time of stress in relation to the oil palm crop phenology. The stages of growth are sensitive towards these stresses during the initial inflorescence and fruit development phases.

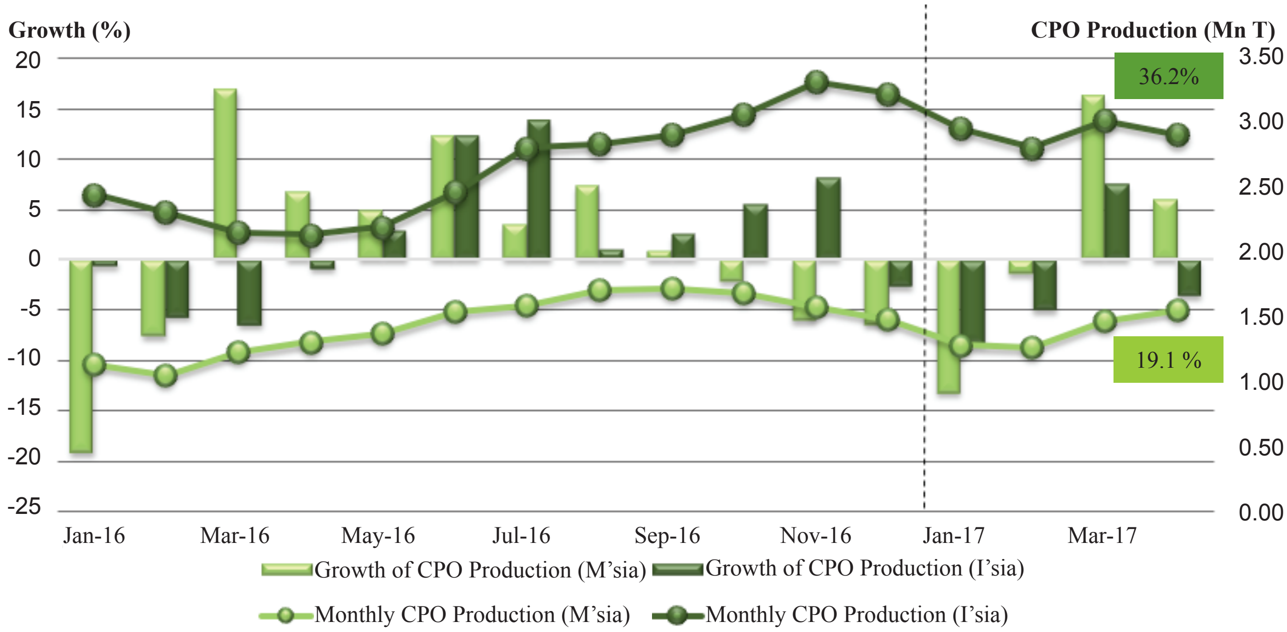
Figure 1 shows a comparison between Malaysia's monthly CPO production and growth with Indonesia's. It is apparent that Indonesia had a greater year-on-year CPO production growth (36.2%) whereas Malaysia's growth in CPO production only increase by 19.1% over the same period.

Thus, the impact of the *El Niño* on the Malaysian palm oil industry during this cycle was stronger than it was in Indonesia. By the second half of 2016, Indonesia palm oil industry was starting to recover by showing positive growth, meanwhile Malaysia was in opposite situation in which experiencing negative growth of CPO production.

Figure 2 shows the link between the highest maximum temperature and the performance of Malaysia's palm oil production from 1995 to 2017. The dotted red line represents the highest maximum temperature for oil palm leaves to grow and function efficiently (Woittiez *et al.*, 2017). Year 1998 showed a huge reduction in CPO production from 9.07 million tonnes in 1997 to 8.32 million tonnes due to the *El Niño* phenomenon in Malaysia before production went up by 26.8% in 1999. 2002 and 2010 recorded slightly lower CPO production due to the moderate *El Niño* phenomenon. If the same pattern occurs as it did 20 years ago, CPO production in 2017 is expected to be reduced by more than two million tonnes.

Ayat *et al.* (2013) studied the impact of *La Niña* and *El Niño* events on crude palm oil prices. They found that past *El Niño* events (at a lag of 8-22 months) can affect current CPO production. When *La Niña* and *El Niño* events occur, CPO production and stock level in a particular year will be reduced by 3.37% and 2.5%, respectively, while CPO price is increased by 10.2% as compared with a normal situation. In studying the impact of *La Niña* and *El Niño* events on CPO prices, a forecasting model for CPO prices was developed which includes elements of *La Niña* and *El Niño* by using multiple regression analysis.

On the other hand, by using national crop and livestock production records from 1961-2003, and satellite-derived data on pasture greenness from 1982-2003, the productivity of crops, livestock and pastures in Africa was predictably associated with ENSO and the north Atlantic oscillation. It was suggested that African food production will be reduced if the global climate changes towards more *El Niño*-like conditions, as has



Source: Christian Schmollinger, 2017, Reuters (for data on Indonesia) & MPOB 2017 (for data on Malaysia).

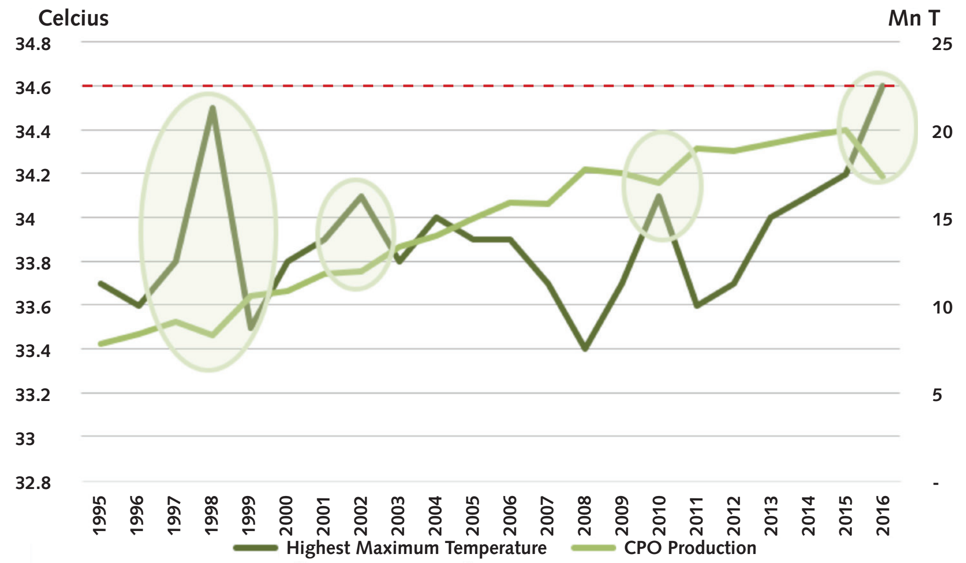
Figure 1. Malaysia Vs Indonesia Monthly CPO Production and Growth.

been predicted by most climate models (Stige *et al.*, 2006).

In Indonesia, the associations among sea surface temperature anomalies (SSTAs), rainfall and rice production were measured over the past three decades. During strong *El Niño* years, production shortfalls in the wet season were not made up later in the crop year (Naylor *et al.*, 2001).

Nadia and Syuhadatul (2016) studied the development of the ENSO event and analysed its impact on the palm oil industry in Malaysia. Climate variability does significantly influence the palm oil production pattern in Malaysia but the impact is subject to the intensity of the *El Niño* and *La Niña* events. A moderate or strong *El Niño* can cause rainfall to be lower than normal, hence affecting the oil palm production pattern. The results from a linear regression analysis suggest that there is no significant relationship between rainfall and CPO price. However, CPO production does affect the movements in CPO price. For every 1% decline in CPO production, CPO price will increase by 0.04%.

Haniff *et al.* (2016) investigated the relationship between rainfall and FFB yield in three different regions in Malaysia by using the Pearson correlation technique. The study shows that FFB yield was affected by the low rainfall during severe *El Niño* events and excessive rainfall during *La Niña*



Source: MPOB (2016).

Figure 2. Highest maximum temperature and Malaysia's CPO production (1995 – 2017 movements).

events. However, the severity of an *El Niño* event was largely determined by the number of months with less than 100 mm rainfall, which had been very low since 2007. The reduction in FFB yield from the recent weak or moderate *El Niño* events was minimal.

To sum up, this study aimed to extend the findings of Haniff *et al*. (2016) who only investigated the correlations among FFB production, *El Niño* and *La Nina* events. The extension incurred the adoption of the econometric technique called a Vector Error Correction Model (VECM) which adjusts short-run changes in variables and deviations from the equilibrium.

METHODOLOGY

The model was established with three variables and hypothesised that CPO production is a function of FFB yield (FFB YIELD) and Oceanic Niño Index (ONI):

Equation (1)

$$CPO_t = F(FFB\ yield_t, ONI_t)$$

where CPO represents monthly CPO production in Malaysia (in tonnes), while 't' sign is the time trend.

The data covering 120 months from 2007 to 2016 were obtained from the MPOB database. Data on CPO production and FFB yield were converted into natural logarithms to minimise the variations.

Stationarity of a series is important because it can influence its behaviour. The simple ordinary linear square (OLS) model (equation 2) is a spurious regression as the model ignores the stationary process. Thus, the relationship between x and y can be considered unreliable even when there is a theoretical relationship.

Equation (2)

$$Y_t = \alpha + \beta X_t + \varepsilon_t$$

If the mean and variance are constant over time, then the series is said to be a stationary process (having no unit root). Differencing a series using differencing operations produces another set of observations as shown below:

Equation (3)

x level	x_t
x with 1st difference	$x_t - x_{t-1}$
x with 2nd difference	$x_t - x_{t-2}$

If a series is stationary at level it is denoted as I (0), or integrated to the order 0. If a series that is stationary after differencing once, it is designated as I (1) or integrated to the order one (1). This study used the Augmented Dickey-Fuller (ADF) approach (Dickey and Fuller, 1979) and the Phillips-Perron (PP) approach (Phillips and Perron, 1988) to test stationarity of the series.

The Johansen and Juselius (1990) co-integration test is designed to determine the number of co-integration vectors by using the Maximum Eigenvalue test and the Trace test. It also implies that a long-run relationship among the variables exists. Maximum Eigenvalue and Trace test the null hypothesis of cointegrating relation between the variables. In some cases, Trace and

Maximum Eigenvalue statistics produce different results on the number of co-integrating vectors. Alexander *et al*. (2002) suggested that the results of the Trace test be considered in such instances.

If co-integration is detected from the Johansen and Juselius test, it means that a long-run equilibrium relationship between the variables exists. Thus, we may apply VECM to evaluate the short-run properties of co-integrating series. If there is no co-integration, VECM is no longer required, and we may proceed to the Granger causality method to test the causality link between the variables. The regression equation form for VECM is as follows:

Equation (4)

$$\Delta Y_t = \alpha_1 + p_1 e_{t-1} + \sum_{i=0}^{n} \beta_i \Delta Y_{t-i} + \sum_{i=0}^{n} \delta_i \Delta X_{t-i} + \sum_{i=0}^{n} \partial_i \Delta Z_{t-i}$$

where Y represents CPO production, X represents FFB yield performance and Z represents ONI. A negative and significant coefficient for ECM (*i.e.* in the above equation) indicates that any short-run fluctuations between the independent variables and the response variable will give rise to a stable long-run relationship between the variables.

RESULTS AND DISCUSSION

Prior to testing for co-integration, the study conducted a test on the order of integration for each variable using ADF and PP procedures to examine data stationarity, and consequently determine the existence of a unit root. *Table 1* indicates that based on the ADF test, the calculated t-test for Log of Crude Palm Oil (LCPO), FFB yield and ONI is smaller than the critical value in the level form, suggesting this variable to be stationary after differencing once I (1) when showing a greater t-statistic than the critical value.

Co-integration rank was estimated by using the Johansen and Juselius methodology. The co-integration rank can be formally tested with the Trace and Maximum Eigenvalue statistics. The results shown in *Table 2* suggest that lag 2 be used, based on the Schwarz information criterion (SC). As the rank is equal to 1 (*Table 3*), which is more than zero and less than the number of variables, the series were co-integrating among the variables. In spite of that, we proceeded to adopt the VECM model.

The vector error correction model (VECM) used is as follows:

$$D(LCPO) = -0.233ECT^{***} + 0.175D(LCPO_{t-1})^{***} + 0.440D(LCPO_{t-2})^{***} + 0.183D(LFFB_{t-1}) - 0.103D(LFFB_{t-2}) - 0.013D(ONI_{t-1}) + 0.007D(ONI_{t-2}) + 0.0005$$

TABLE 1. UNIT ROOT TESTS (WITH INTERCEPT)

Variable	Level		First difference	
	ADF	PP	ADF	PP
LCPO	-2.342	-3.083**	-4.177***	-8.658***
FFB Yield	-1.960	-4.293***	-4.226***	-8.798***
ONI	-5.559***	-3.522***	-6.152***	-5.361***

Note: *significant at 10% level, **significant at 5% level, ***significant at 1% level.
ADF: Augmented Dickey-Fuller, PP: Phillips-Perron.

TABLE 2. OPTIMUM LAG LENGTH SELECTION

Lag	LogL	LR	FPE	AIC	SC	HQ
0	73.64652	NA	5.94e-05	-1.218044	-1.146830	-1.189135
1	403.9342	637.7969	2.33e-07	-6.757486	-6.472632	-6.641852
2	471.1622	126.3423	8.55e-08	-7.761418	-7.262923*	-7.559057
3	491.0461	36.33950	7.09e-08	-7.949071	-7.236936	-7.659985*
4	500.5901	16.94880*	7.04e-08*	-7.958450*	-7.032674	-7.582638

Note: *significant at 10% level, **significant at 5% level, ***significant at 1% level.
LR: sequential modified LR test statistic (each test at 5% level).
FPE: final prediction error.
AIC: Akaike information criterion.
SC: Schwarz information criterion.
HQ: Hannan-Quinn information criterion.

TABLE 3. JOHANSEN AND JUSELIUS TEST

Lags interval (in first differences): 1 to 3				
Hypothesised	**Eigenvalue**	**Trace statistic**	**0.05 critical value**	**Probability****
None *	0.317190	54.36838	29.79707	0.0000
At most 1	0.048050	9.728433	15.49471	0.3022
At most 2 *	0.033338	3.967028	3.841466	0.0464
Maximum Eigenvalue				
Hypothesised	**Eigenvalue**	**Max-Eigen statistic**	**0.05 critical value**	**Probability****
None *	0.317190	44.63995	21.13162	0.0000
At most 1	0.048050	5.761405	14.26460	0.6440
At most 2 *	0.033338	3.967028	3.841466	0.0464

Note: *significant at 10% level, **significant at 5% level, ***significant at 1% level.

The error correction term (ECT) is supposed to be negative and significant. This is mainly because a negative ECT coefficient value will show how quickly an adjustment is needed in a short-run disequilibrium towards achieving a long-run equilibrium. In this case, the ECT coefficient value showed a negative value and was highly significant. Thus, it can be concluded that for each month, a 23.3% adjustment is needed in a short-run disequilibrium towards achieving a long-run equilibrium. The changes in CPO production were significantly influenced by FFB yield and ONI.

The impulse response function (IRF) was used as a recheck of the co-integration test findings. Orden and Fisher (1993) found that identification of restrictions is employed to draw a meaningful interpretation. It was shown that the response of a variable results from the impulse of the endogenous variable. A shock in a dependent variable brings about a positive or negative direction in the explanatory (independent) variables. When the response is LCPO, then every response, if there is inflation, is positive for FFB yield and negative for ONI. Responses in FFB yield had a positive trend while ONI had a negative trend because of the shock in LCPO.

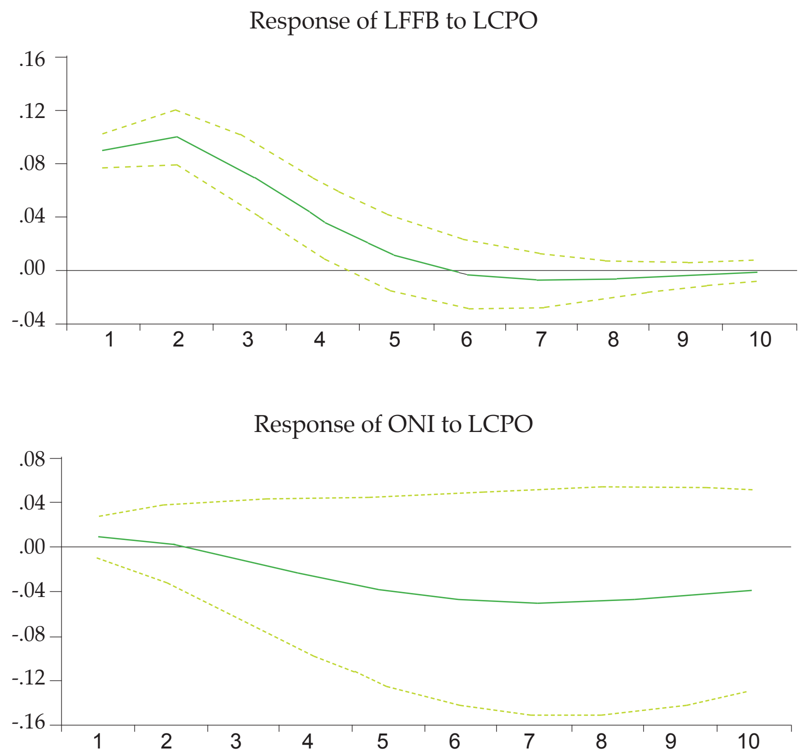


Figure 3. Response of exogenous variables towards the endogenous variable.

CONCLUSION

This study presents an analysis of the relationship of CPO production with FFB yield and with the ocean Niño index using the time series Vector Error

Correction Model (VECM) approach. The empirical findings are that, in the long run, Malaysia's CPO production was much influenced by FFB yield and the ocean Niño index. Any deviation from the long-run equilibrium is corrected by 23.3% over each month. The value 0.233 indicates a medium rate of convergence from the equilibrium. Changes in CPO production were significantly influenced by FFB yield and ONI. Hence, this study will be able to help policymakers to be aware of effect of extreme weather and its implications on palm oil production, and of the need to implement a better irrigation system or in-depth R&D on advance technologies which can offset this phenomenon.

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