International Journal of
Geo-Information

Article

Spatial–Temporal Evolution and Analysis of the Driving Force of Oil Palm Patterns in Malaysia from 2000 to 2018

Wenhui Li [1,2,3,4], Dongjie Fu [2,5,6,*], Fenzhen Su [1,2,5] and Yang Xiao [2,5,7]

1 Faculty of Geomatics, Lanzhou Jiaotong University, Lanzhou 730070, China; liwh@lreis.ac.cn (W.L.); sufz@lreis.ac.cn (F.S.)
2 State Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China; xiaoy@lreis.ac.cn
3 National-Local Joint Engineering Research Center of Technologies and Applications for National Geographic State Monitoring, Lanzhou 730070, China
4 Gansu Provincial Engineering Laboratory for National Geographic State Monitoring, Lanzhou 730070, China
5 Collaborative Innovation Center of South China Sea Studies, Nanjing University, Nanjing 210093, China
6 Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai), Zhuhai 519082, China
7 School of Geography and Ocean Science, Nanjing University, Nanjing 210023, China
* Correspondence: fudj@lreis.ac.cn; Tel.: +86-10-64889676

Received: 3 March 2020; Accepted: 22 April 2020; Published: 24 April 2020

Abstract: Oil palm is the main cash crop grown in Malaysia, and palm oil plays an important role in the world oil market. A number of studies have used multisource remote sensing data to conduct research on oil palms in Malaysia, but there are a lack of long-term oil palm mapping studies, especially when the percentage of oil palm tree cover was higher than other plantations in Malaysia during the period of 2000–2012. To overcome this limitation, we used the Google Earth Engine platform to perform oil palm classification based on Landsat reflectance data. The spatial distribution of oil palms in Malaysia in five periods from 2000 to 2018 was obtained. Then, the planting center of gravity transfer method was applied to analyze the expansion of oil palms in Malaysia from 2000 to 2018 using Landsat data, elevation data, oil palm planting area, crude palm oil price, and other statistical data. Meanwhile, the driving factors affecting the change in oil palm planting area were also analyzed. The results showed that: (1) During 2000–2018, the oil palm planted area in Malaysia increased by 5.06 Mha (million ha), with a growth rate of 83.50%. Specifically, the increased area and growth rate for West Malaysia were 2.05 Mha and 62.05% and for East Malaysia were 3.01 Mha and 109.45%, respectively. (2) Three expansion patterns of oil palms were observed: (i) from a fragmented pattern to a connected area, (ii) expansion along a river, and (iii) from a plain to a gently sloped area. (3) The maximum shift of the center of gravity of the oil palms in West Malaysia was 10 km, while in East Malaysia, it reached 100 km. The East Malaysia oil palm planting potential was greater than that of West Malaysia and showed a trend of shifting from coastal areas to inland areas. (4) Malaysia's oil palms are mainly planted in areas below 100 m above sea level; although a trend of expansion into high altitudes is visible, oil palm plantings extend to areas below 300 m above sea level. (5) Topography, crude palm oil prices, and deforestation are closely related to changes in oil palm planted area.

Keywords: Malaysia; oil palms; Google Earth Engine; Landsat

1. Introduction

Palm oil, pressed from the fruit of oil palms, is one of the most important components of the world oil market and accounts for more than 30% of global fats and vegetable oil production [1].

In 2004, palm oil became the most important oil product in the world in terms of production, trade, and consumption. According to the statistics of the Food and Agriculture Organization (FAO) of the United Nations, the oil palm planting area in Southeast Asia accounted for approximately 71% of the total oil palm planting area in the world in 2017 [2].

In the early 19th century, Malaysia established the first oil palm plantation in Southeast Asia [3]. In 1966, Indonesia and Malaysia began to dominate the global palm oil trade [4]. Since the 1990s, with the implementation of the United Nations framework for "Reducing Emissions from Deforestation and Forest Degradation (REDD)", the relationship between crop expansion and deforestation has become the focus of many experts [5]. In the 21st century, to promote the sustainable development of the oil palm industry, the round table on sustainable palm oil (RSPO) was established.

The continuous expansion of oil palm plantations not only leads to large changes in land use types [6], but also seriously threatens the environment, including reduced biodiversity in forest ecosystems [7], increased greenhouse gas emissions [8], and water pollution [9]. Due to the large-scale impact of palm oil expansion and the significance of this impact, a number of related studies have applied remote sensing data for, for example, determining the number of trees planted in oil palm plantations [10], monitoring changes in the planting area [11], establishing the age of oil palm trees [12], identifying carbon flux [13] or above ground biomass (AGB) [14], pest detection [15], yield estimation [16], and assessment of other factors. Previous research has analyzed the opportunities and challenges that the oil palm industry will face in the future [17] and has explored the sustainable development of the oil palm plantation industry [18]. Oil palms grow in cloudy and rainy areas. Previous studies have mostly combined optical data with microwave remote sensing data for oil palm classification (e.g., Landsat and advanced land observing satellite phased array L-band synthetic aperture radar (ALOS PALSAR)). For example, Cheng et al. [19] supplemented PALSAR data with Landsat data; the distribution of oil palms in Malaysia was obtained by using the support vector machine and Mahalanobis distance methods, and changes in oil palm planting area in Malaysia during 2007–2016 were analyzed in combination with digital elevation model (DEM) data. Tan et al. [13] combined ALOS PALSAR data with the optical remote sensing data of the Disaster Monitoring Constellation 2 from the United Kingdom (UK-DMC2) to classify the age of oil palm trees using a variety of classification techniques, providing a scientific basis for predicting oil palm productivity and carbon emissions. However, in the case of the natural tree cover had the highest loss percentage compared to other land cover types between 2000 and 2012 [20], there are a lack of studies focusing on long-term oil palm mapping in Malaysia, especially. The study of long time series of optical remote sensing imagery requires a lot of computing resources, especially over large areas, and traditional stand-alone computing resources have difficulty meeting this demand. The rapid development of high-performance computing platforms in the field of geosciences, such as Google Earth Engine (GEE) [21], NASA Earth Exchange (NEX) [22], and Descartes Labs, makes it possible to use the same type of optical sensor (such as the Landsat series) to map the temporal and spatial distribution of multiperiod objects on a regional/national scale and to perform the subsequent analysis.

To improve our understanding of long-term spatial variation of oil palms in Malaysia, this study mapped the spatial-temporal variation of oil palms in five periods (2000–2018) via the land cover sample collection platform Collect Earth Online (CEO) and the planetary-scale earth science data and analysis platform GEE. The land cover reference data contained sample points obtained from 2018 field trips and high spatial resolution images in different years, such as Digital Global and Bing Maps in the CEO platform. Using the classification and regression tree (CART) method, the spatial distribution of oil palms in 2000, 2005, 2009, 2015, and 2018 was obtained and verified. This study also compared the results with the statistics of the FAO, the Malaysia Palm Oil Board (MPOB), and the results from the distribution of former oil palm plantations to verify the results from this study. Finally, a dynamic spatial and temporal analysis of oil palm distribution changes was carried out, and the factors affecting the expansion of the oil palm planting area were explored from the aspects of altitude, price, and deforestation.

2. Materials and Methods

2.1. Study Area

Located in Southeast Asia, Malaysia is between the Pacific Ocean and the Indian Ocean. It is divided into East Malaysia and West Malaysia by the South China Sea (Figure 1). Most of Malaysia's coastal areas are plains, while the central part is a plateau covered with dense tropical rainforests [23]. West Malaysia accounts for approximately 40% of the country's land area, and mountains extend from the interior to the periphery. The tropical rainforest of Kalimantan in East Malaysia is the second largest tropical rainforest in the world, second only to the tropical rainforests of the Amazon basin in South America [24]. According to the Köppen climate classification [25], Malaysia has a tropical rainforest climate with high temperatures and rain throughout the year. The annual precipitation is over 2000 mm, which produces advantageous conditions for oil palm growth. Malaysia has been growing oil palms on a large scale since the 1960s. In the mid-1960s, the government encouraged private individuals to replant arable land, old rubber plantations, and old coconut gardens into oil palm plantations [26].

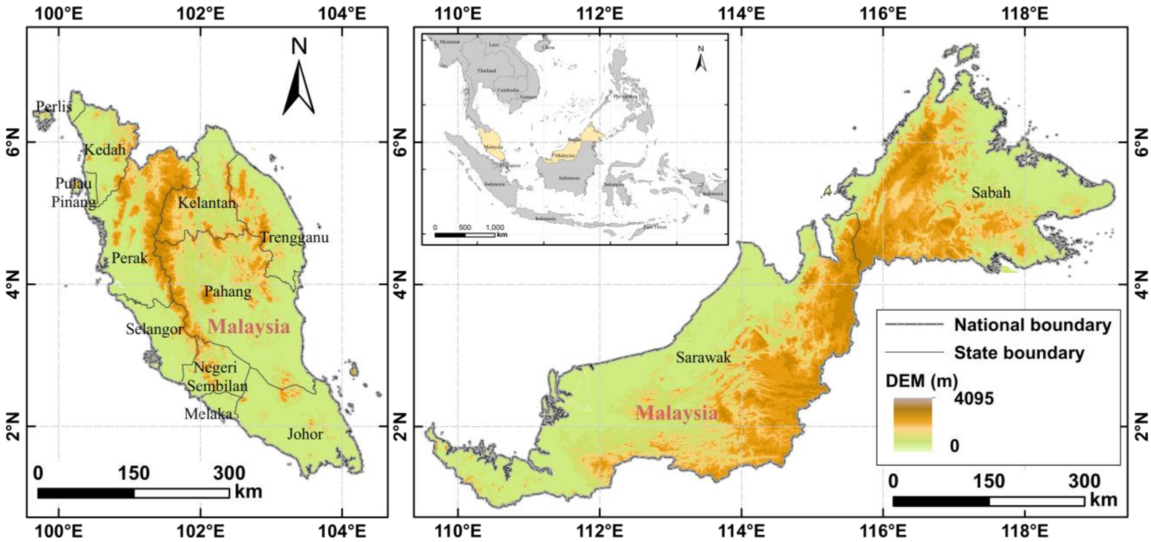

Figure 1. Map of the study area, showing its geographical location, topography, and elevation. DEM, digital elevation model.

2.2. Data Preprocessing and Platform

The GEE platform—a planetary-scale geospatial analysis platform launched by Google—was applied to the oil palm mapping in 2000, 2005, 2009, 2015, and 2018. Compared with traditional remote sensing image processing software, GEE stores data in the cloud and has direct access to multisource remote sensing data (e.g., from a moderate-resolution imaging spectroradiometer (MODIS), Landsat, and Sentinel) and high-resolution images, as well as climate, land cover, resource and environment, geophysical, and socioeconomic datasets. The data can be continuously updated to ensure real-time analysis and usefulness of the results [21]. The online JavaScript API provided by GEE allows users to call functions and provides access to a variety of data, such as vector data, raster data, and charts. Users can employ the GEE algorithms or construct new algorithms for analysis and visualization, and GEE has been widely used for predicting crop yields, monitoring global forest changes, and monitoring climate change [27].

The CEO used for sample selection is a tool for geoscience analysis. It provides global high spatial resolution image data from Digital Global, Planet Lab, and Bing Maps, as well as access to current and historical changes in land dynamics around the world. It plays an important role in the monitoring of land use change, the assessment of natural disasters, and the sustainable management of scarce resources. It can meet the needs of its users online in terms of, for example, land use classification and natural disaster prediction [28].

The remote sensing data used in this study were Landsat 4, 5 Thematic Mapper (TM), and Landsat 8 Operational Land Imager (OLI) Tier 1 surface reflectance data (spatial resolution: 30 m; date: 2000, 2005, 2009, 2015, and 2018; cloud coverage percentage: less than 30%). Landsat 7 ETM+ data with Scan Line Corrector (SLC)-off strips were not used in this study. To capture cloudless images that cover the study area, the selection date for Landsat image synthesis was extended to one year before and after the study period. Each pixel of the Landsat synthetic data corresponds to the pixel on the median date in the available Landsat time series. Figure 2 shows the scenes of annual Landsat synthetic images using short-wave infrared (SWIR)-near-infrared (NIR)-red as red-green-blue composites. Wherein, each pixel of the annual Landsat synthetic data is the pixel corresponding to the median date on the available time series Landsat data.

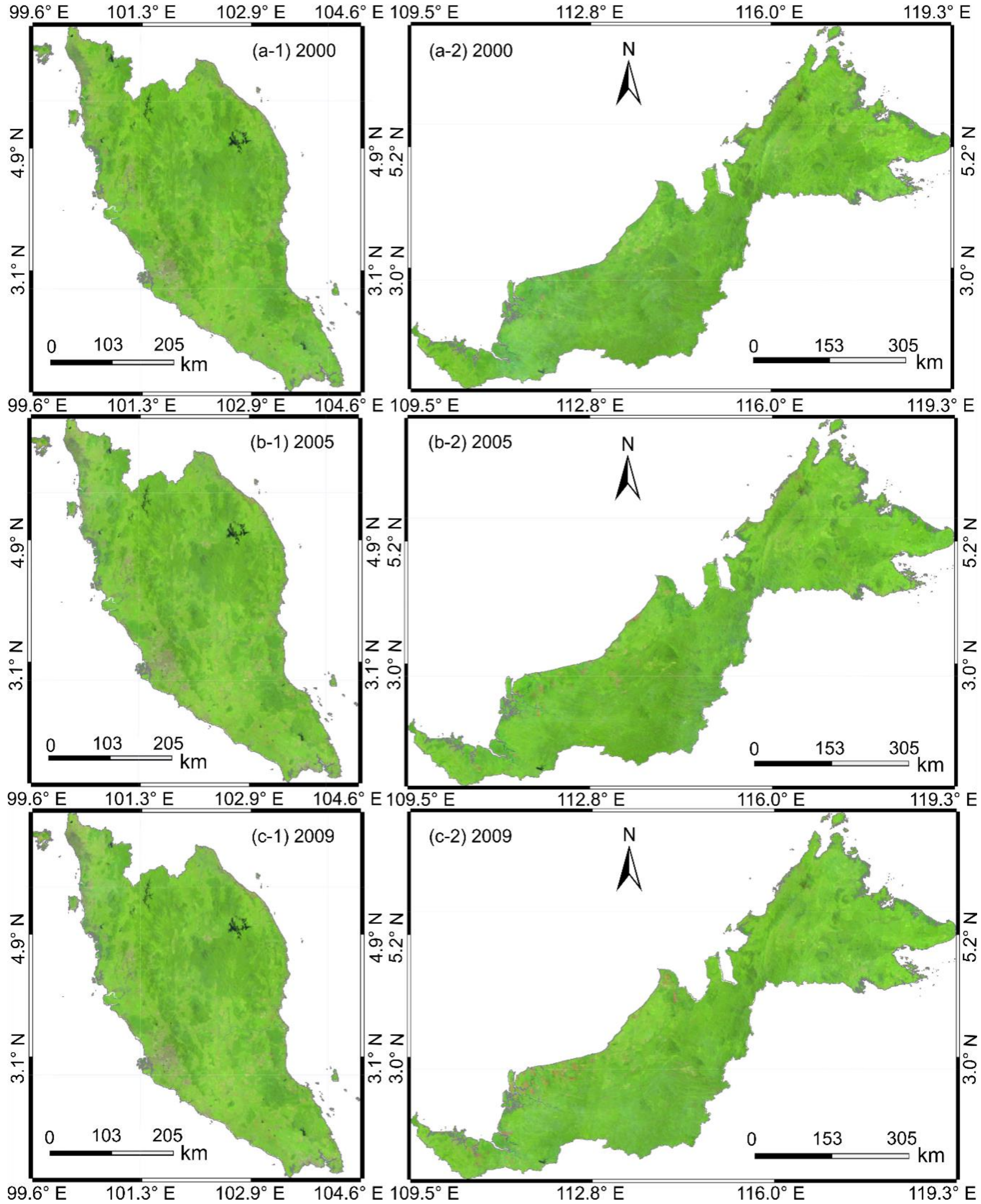

Figure 2. *Cont.*

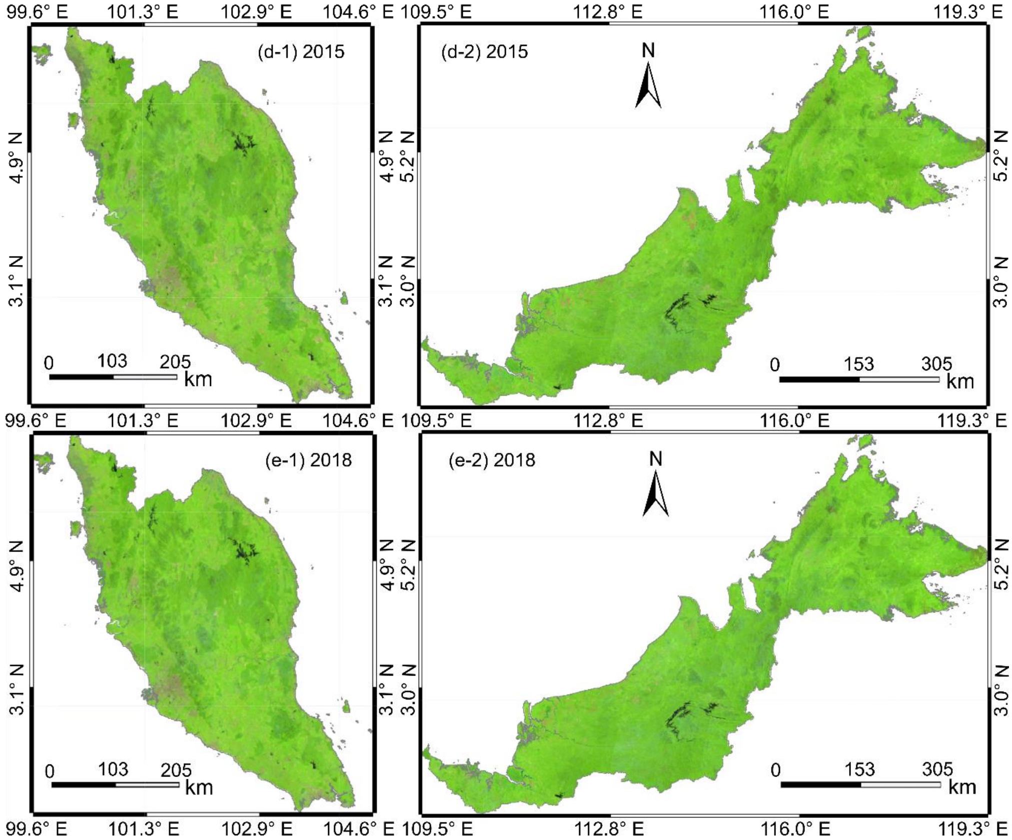

Figure 2. Short-wave infrared (SWIR)-NIR-red composite of annual Landsat synthetic image for classification.

The maximum cloud coverage of the Landsat image used in this study was 30%. The cloud coverage of images in 2018 and 2015 were less than 15%, in 2000 and 2005 less than 20%, and in 2009 less than 30%.

The elevation data used in this study were from the shuttle radar topography mission (SRTM v3) [29] with a spatial resolution of 1 arc second (approximately 30 m), which were provided by The National Aeronautics and Space Administration (NASA), National Geospatial-Intelligence Agency (NGA), and the aerospace sector in Germany and Italy. SRTM data are widely used in the study of topography, hydrology, and land cover [30].

In addition to remote sensing data and elevation data, this study also combined spatial data, such as Malaysian administrative boundaries, and statistical information, such as the Malaysian statistical yearbook. Malaysia's national administrative border and state administrative boundaries were derived from the Office of the American Geographer. The land area of the states of Malaysia and the oil palm planting area data during 2000–2018 were derived from the FAO and the MPOB. The price of crude palm oil during 1998–2018 came from the Malaysian Bureau of Statistics.

2.3. Methods

2.3.1. Oil Palm Planting Area Extraction

(1) Sampling design

According to the research of Olofsson et al. [31,32], stratified random sampling was used in this study. The training and validation sample data were divided into oil palm, forest (including natural forests, plantations other than oil palm forest, and other vegetation such as bushes), water, and other land cover types (including construction land, bare land, cultivated land, salt fields, and breeding areas). Before selecting the sample points, with reference to the standard error of classification targets proposed by Olofsson et al [32], we specified a target standard error for overall accuracy of 0.01. We conjectured that user's accuracies of oil palms and others land use types would be 85%, and of forests and water would be 90%. Based on this goal, we calculated the minimum number of sample points required for each type of land use to ensure that the number of sample points in the actual sampling was higher than the estimated minimum.

First, according to geographic location, Malaysia was divided into East Malaysia and West Malaysia. Second, according the Spatial Database of Planted Trees (SDPT) [33], the number of large oil palm plantations in East and West Malaysia in 2018 was calculated separately. Taking West Malaysia as an example, we divided the total area of oil palm plantations (data source: FAO) in West Malaysia by the number of plantations to calculate the average area of one oil palm plantation. Then, the land area of West Malaysia was divided by the average area of a single oil palm plantation to get the number of plantations needed to cover the entire territory of West Malaysia. Assuming that oil palms in different plantations are different ages, at least one sample point should be selected for one plantation to estimate the number of sample points needed. The same method was applied to obtain the number of sample points in East Malaysia. Third, referring to Cheng et al. [34], using the global grid system for layering when selecting sample points, we divided the study area into grids. The number of grids was equal to the number of calculated samples. One sample point was randomly generated in each grid; this ensures both the wide distribution and the randomness of sample points. In addition, oil palms of different ages have different spectral characteristics; thus, to ensure that the selected sample points contain different ages, the number of sample points were added according to the large oil palm plantation data in 2018 from SDPT, and the position of the sample points under cloud coverage or the grid lacking high-resolution images were adjusted.

After manually checking the sample points and removing the sample points from areas with cloud cover, 2130 available sample points were retained from the 2767 sample points randomly generated by GEE using simple random sampling and the Malaysia field survey data from 2018. In the other four periods, the number of sample points was adjusted according to the quality of the high-resolution images. Seventy percent of the total number of sample points was randomly selected as training points, and 30% were used as verification points. The number of selected sample points is shown in Table 1.

Table 1. The number of sample points.

	Actual Number of Sample Points					Minimum Number of Sample Points
	2000	**2005**	**2009**	**2015**	**2018**	
Oil palm	542	547	571	590	653	361
Forest	929	1002	1000	1140	1163	613
Water	88	90	91	108	115	19
Others	192	203	185	190	199	46
Total	1751	1842	1847	2028	2130	1039

The distribution of the sample points is shown in Figure 3.

By comparing the high-resolution remote sensing satellite imagery data from companies such as Digital Global and Airbus in Google Earth, it was found that in Sarawak and central Sabah, to facilitate the cultivation of oil palm trees and the picking of oil palm fruits, the mountains in tropical forest areas were redeveloped into stepped artificial forest land. Due to the clustered distribution of 1–3-year-old oil palms, the young oil palm forest land (Figure 4a,b) was difficult to distinguish from the stepped forest land (Figure 4c) and bare ground (Figure 4d) in hilly areas. This study was concerned with the typicality of the selected sample points, and the number of sample sites in complex land cover types in East Malaysia such as bare land and hilly areas with weeds might not be sufficient. This situation may have led to some of the bare land and grassland in Sarawak and central Sabah being misclassified into young oil palm forestland, which may cause the extracted oil palm area in some areas to be higher than the statistical area.

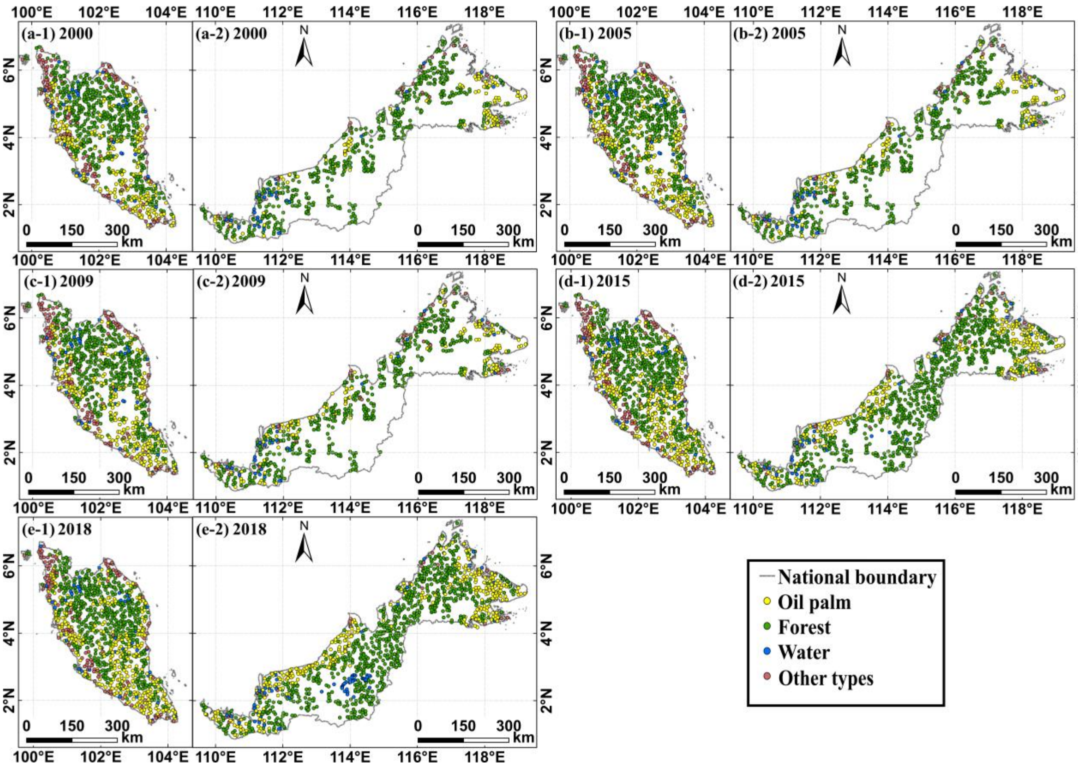

Figure 3. Distribution of the Malaysian sample points. The letters a, b, c, d, and e represent 2000, 2005, 2009, 2015, and 2018. The numbers 1 and 2 represent West Malaysia and East Malaysia, respectively.

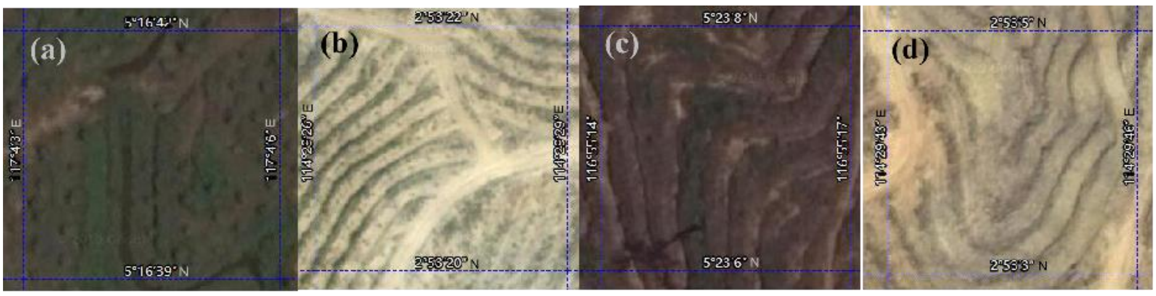

Figure 4. High-definition images with similar characteristics: (**a**,**b**) oil palm ground; (**c**) woodland; and (**d**) bare ground.

(2) Classification method

There are many methods for classifying remote sensing images. In the classification process, different classification methods produce different results. To find the classification method most suitable for this research, three kinds of classification methods—random forest (RF), support vector machine (SVM), and CART—were used in this study. By comparing the classification results of the five stages of the three classifiers, the results show that in the five classification periods, the lowest overall accuracy of RF classification (79%) and of SVM classification (75%) was lower than that of the CART method (87%). The three classification results were compared with digital images from Digital Global and Bing Maps, based on which the CART method, which had the best overall classification accuracy, was selected.

In the classification process, with reference to the study of oil palm mapping by McMorrow et al. [12], Lee et al. [35], Morel et al. [36], and Wahid et al. [37], and according to oil palm growth condition and the features of oil palm planting area in the image, we selected different combinations of feature information for testing. Finally, this research used spectral information, including blue, green, red, near-infrared, and shortwave infrared surface reflectance bands, normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and topographic information, including slope, aspect, and elevation. In addition, we also used texture information, i.e., the measurement of spatial correlation through spatial neighborhood analysis in GEE [38].

(3) Post-classification processing and accuracy verification

After obtaining the classification results for 2000, 2005, 2009, 2015, and 2018, this study used a method based on the mathematical morphology of the model. Eight-neighbor analysis was performed on a pixel-by-pixel basis, merging the scattered patches obtained after classification. Then, we separately calculated the area of the four types of land use: oil palm, forest, water, and other.

This research used 30% of the selected sample points as data with which to verify the accuracy of the oil palm classification results. The number of verification sample points in 2000, 2005, 2009, 2015, and 2018 were 345, 462, 464, 608, and 639, respectively. A confusion matrix was used to analyze the classification results, and the accuracy of the oil palm classification results was verified by the overall accuracy (OA), producer's accuracy (PA), and user's accuracy (UA).

2.3.2. Calculation of the Center of Gravity of Oil Palm Planting Space

In order to obtain the direction of oil palm expansion between states, we studied the main areas of oil palm plantation in different periods and calculated the shift path of the oil palm planting center of gravity. The regional center of gravity is an indicator of the overall distribution of an attribute in a region [39], and it is usually expressed by some attribute and geographic coordinates of each sub-area within the region. Suppose an area consists of n sub-areas, where the center of gravity of the i-th sub-area is (X_i, Y_i), and W_i is the quantity of a certain attribute of the sub-area. Then, the mean geographic coordinate space (X, Y) is the geometric center (the center of gravity) of a certain attribute in the region. The corresponding center of gravity coordinate migration formula is [40]:

$$X = \frac{\sum XiWi}{\sum Wi}, Y = \frac{\sum YiWi}{\sum Wi} \quad (1)$$

This study used the spatial center of gravity transfer model to calculate the center of gravity of the oil palm planting area, compared the locations of the center of the oil palm planting distributions during the study period, analyzed the change in the center of gravity of oil palm planting areas from 2000 to 2018, and studied its expansion direction.

2.3.3. Curve Fitting

Curve fitting is a data mining processing method that approximates the functional relationship of discrete point groups by adopting continuous curves [41]. Discrete point group data include scientific experimental data, and observation data in social or economic activities may be used in scientific research. The curve equation that reveals the inherent law between the dependent variable y and independent variable x is [42]:

$$y = \mathrm{f}\,(x, c) \quad (2)$$

This study used R^2 to represent the goodness of fit of the fitted curve, which refers to how well the regression line fits the observations. The maximum value of R^2 is 1. The closer the value of R^2 is to 1, the better the fit of the regression line to the observed value; on the contrary, the smaller the value of R^2, the worse the fit of the regression line to the observed value [43].

We used the curve fitting method to study the relationship between oil palm plantation and price and deforestation. This study used MATLAB to achieve curve fitting and to calculate the goodness of fit.

3. Results

3.1. Spatial-Temporal Distribution of Oil Palms in Malaysia

3.1.1. Classification Results

According to our classification results, from 2000 to 2018, the oil palm plantation area in Malaysia increased from 5.59 to 11.56 Mha—an increase of 5.98 Mha with a growth rate of 106.96%. The area of oil palm plantations in West Malaysia increased by 2.53 Mha, with a growth rate of 82.77%; in East Malaysia the area increased by 3.45 Mha, with a growth rate of 136.14%. The oil palm planting distribution during 2000–2018 is shown in Figure 5.

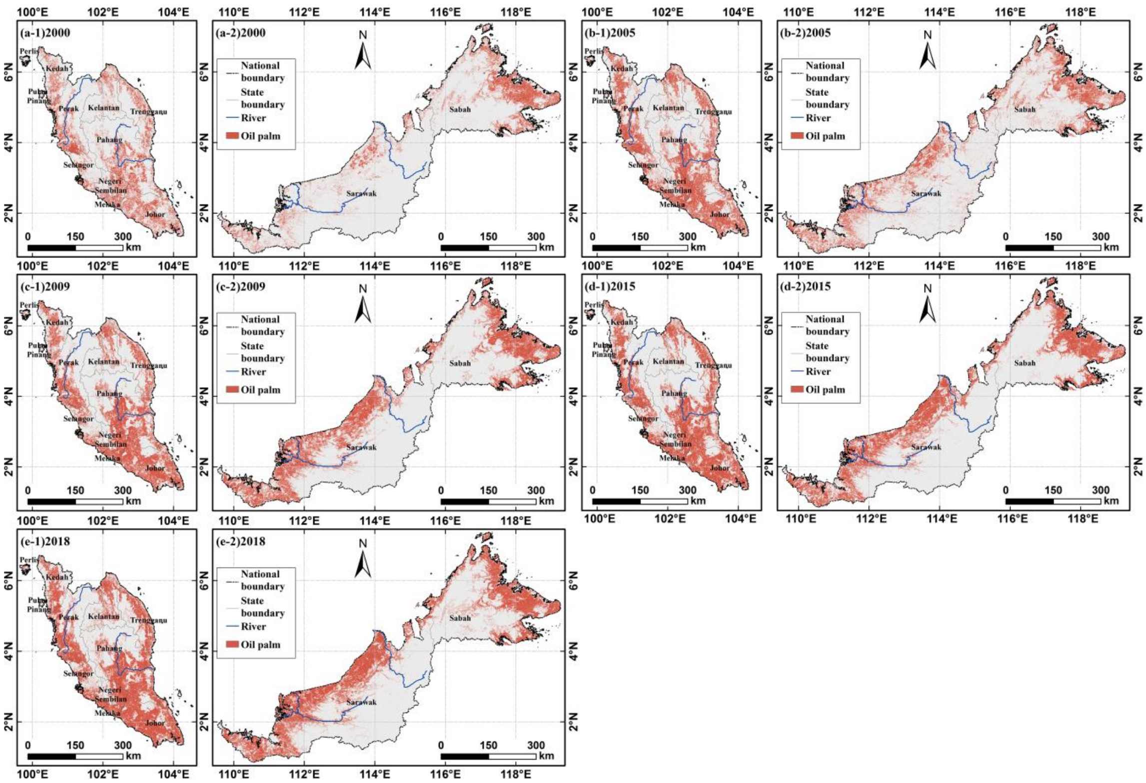

Figure 5. Oil palm planting distribution during 2000–2018. The letters a, b, c, d, and e represent 2000, 2005, 2009, 2015, and 2018, respectively. The numbers 1 and 2 represent West Malaysia and East Malaysia, respectively.

After obtaining the classification results, we adjusted the classification results with reference to Olofsson's method [32]. After adjustment, the oil palm plantation area in 2000 was 6.06 ± 0.82 Mha with a 95% confidence interval, and the area was 11.13 ± 0.81 Mha in 2018. Compared with the results before the accuracy assessment, the planting area increased by 0.48 Mha in 2000, and decreased by 0.29 Mha, 0.99 Mha, 0.16 Mha, and 0.43 Mha in 2005, 2009, 2015, and 2018. We used the results of the accuracy assessment as the final results.

According to the growth of oil palm planting areas in various states from 2000 to 2018 and to the oil palm planting situation in each state (Figure 6), it can be concluded that the overall oil palm planting area in Malaysia is expanding. The average annual growth rate in the first two stages (2000–2005 and 2005–2009) decreased. In addition to Perlis and Johor, the other nine states in West

Malaysia experienced negative growth during 2005–2009. By 2009–2018, the annual growth rate began to increase. The average annual growth rate of oil palm planted area was 6.31% during 2000–2005, which is the highest growth rate during the study period. Between 2005 and 2009, Kedah, Negeri, Perak, Selangor, and other states experienced negative growth, all of which are located in West Malaysia. The planting area of Selangor decreased from 2548.52 to 2076.07 km^2 in 2005–2009, a decrease of 18.54%. Meanwhile, the planting area in Kedah fell from 3053.47 to 2542.46 km^2 in 2005–2009, a decrease of 16.74%. However, the oil palm planting area in Kedah and Selangor increased to varying degrees in 2009–2015. West Malaysia's expansion during the study period was concentrated in Johor, Pahang, and Perak and grew at an average annual rate of 3.02%, 2.97%, and 2.08%, respectively. In addition, the proportion of oil palm planting area in Melaka has historically been the largest among the states; in 2018, the planting area reached 64.63% of the total area of Melaka.

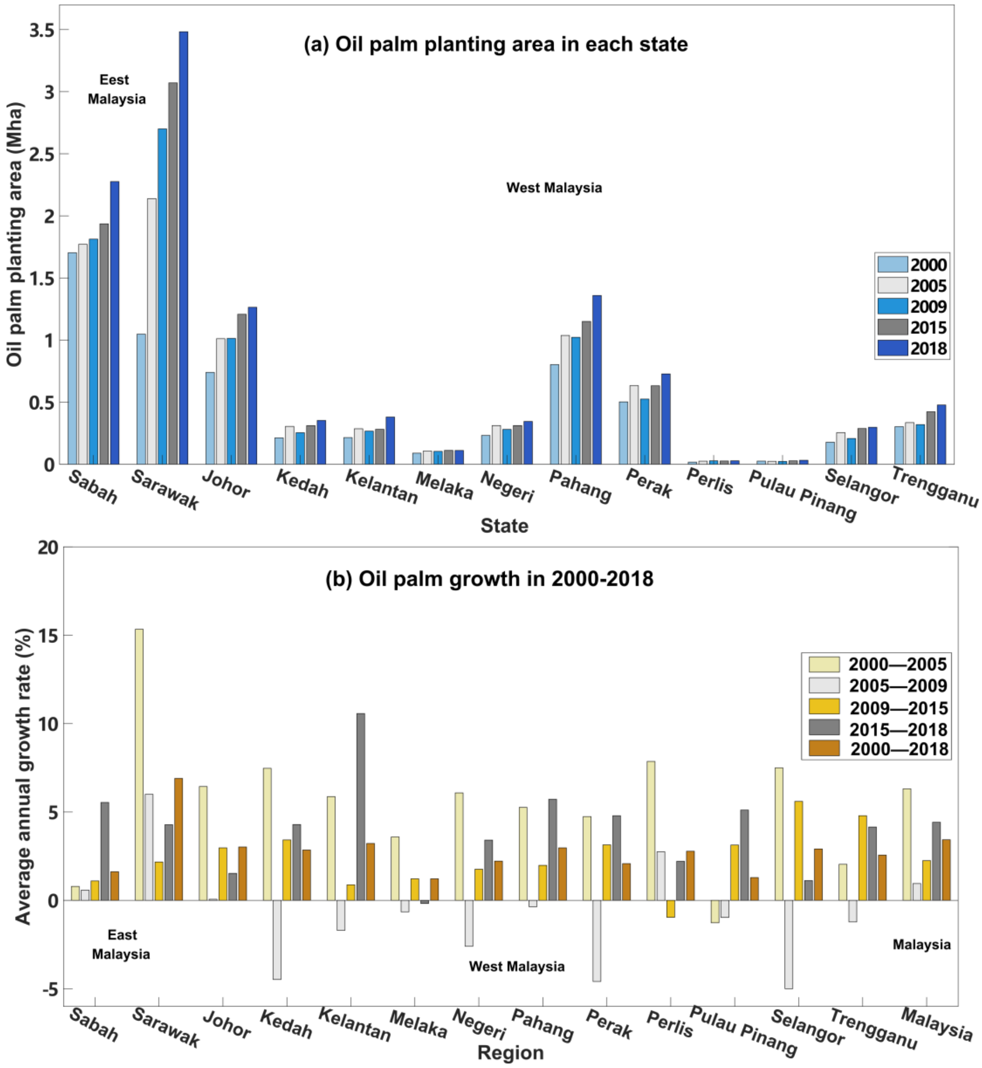

Figure 6. Oil palm planting area in (**a**) each state and (**b**) annual growth rate of oil palm planting during 2000–2018.

In contrast, since 2000, the planting area increased at a rate of 6.90% and 1.62% per year in Sarawak and Sabah, respectively. Although Sabah's growth rate is slightly lower than Malaysia's annual growth rate of 3.42%, the expansion area is still among the highest in the country. As of 2018, the East Malaysia oil palm planting area reached 5.76 Mha, accounting for 51.72% of the total oil palm planting area in Malaysia. The state of Sarawak planted 3.48 Mha, accounting for 30.79% of the state's total area; Sabah planted 2.27 Mha, accounting for 27.98%.

3.1.2. Classification Accuracy

To assess the accuracy of the oil palm classification, this study analyzed the following three aspects: the selection of sample points, the remote sensing image data used for classification, and the classification method.

First, we considered the typicality of the sample points when selecting them and tried to ensure that oil palm trees of all ages were covered. However, for land cover types with a small area and scattered grassland types, such as bare land and weeds, the selected sample points were insufficient. In some cases, the bare ground and weeds were mistakenly divided into the oil palm forest classification. In addition, this research selected Landsat images with less than 30% cloud cover and encompassed all of Malaysia to synthesize the data; however, there were still a small number of cloud-covered areas in the central part of Pahang, central Sarawak, and Sabah, which reduced the classification accuracy in these areas. We also conducted experiments on oil palm planting area extracted from three supervised classification methods, and selected the CART classification method as it had the highest classification accuracy.

In this study, the classification accuracy of 2000, 2005, 2009, 2015, and 2018 was calculated according to an error matrix. The OA of the five-year classification reached over 87% each year; meanwhile, the average PA of oil palms was 80.13% and the average UA was 82.29%. The specific calculation results are shown in Table 2 and the accuracy of the classification results are shown in Table 3.

Table 2. The error matrix expressed in terms of the proportion of area used for the sample size and sample allocation planning calculations of 2000, 2005, 2009, 2015, and 2018.

	Classification Verification	**Oil Palm**	**Forest**	**Water**	**Other**	**Total (Row)**
2000	oil palm	0.136	0.029	0.000	0.002	0.168
	forest	0.036	0.709	0.000	0.000	0.745
	water	0.000	0.000	0.014	0.000	0.014
	other	0.009	0.002	0.006	0.057	0.074
	total (column)	0.182	0.740	0.019	0.059	1.000
2005	oil palm	0.202	0.045	0.000	0.009	0.256
	forest	0.041	0.619	0.000	0.005	0.664
	water	0.001	0.001	0.015	0.001	0.018
	other	0.003	0.006	0.000	0.053	0.062
	total (column)	0.247	0.671	0.015	0.067	1.000
2009	oil palm	0.215	0.065	0.000	0.007	0.286
	forest	0.036	0.593	0.000	0.005	0.634
	water	0.000	0.000	0.015	0.000	0.015
	other	0.006	0.002	0.001	0.055	0.065
	total (column)	0.257	0.660	0.016	0.067	1.000
2015	oil palm	0.262	0.038	0.000	0.015	0.315
	forest	0.047	0.605	0.004	0.004	0.660
	water	0.000	0.000	0.018	0.001	0.019
	other	0.001	0.000	0.000	0.005	0.006
	total (column)	0.310	0.643	0.021	0.025	1.000
2018	oil palm	0.285	0.059	0.000	0.003	0.347
	forest	0.046	0.538	0.002	0.005	0.590
	water	0.000	0.000	0.018	0.000	0.018
	other	0.004	0.001	0.000	0.040	0.045
	total (column)	0.334	0.598	0.020	0.048	1.000

Table 3. The accuracy of the classification results during 2000–2018 (95% confidence intervals).

		2000	2005	2009	2015	2018
Overall accuracy (OA)		0.907 ± 0.026	0.883 ± 0.028	0.877 ± 0.029	0.888 ± 0.026	0.885 ± 0.025
Producer's accuracy (PA)	oil palm	0.813 ± 0.023	0.792 ± 0.018	0.750 ± 0.026	0.831 ± 0.116	0.820 ± 0.019
	forest	0.951 ± 0.289	0.932 ± 0.103	0.936 ± 0.059	0.917 ± 0.206	0.912 ± 0.039
	water	1.000 ± 0.001	0.842 ± 0.000	1.000 ± 0.245	0.923 ± 0.468	1.000 ± 0.252
	other	0.769 ± 0.114	0.853 ± 0.151	0.857 ± 0.188	0.857 ± 0.224	0.891 ± 0.175
User's accuracy (UA)	oil palm	0.804 ± 0.081	0.819 ± 0.073	0.832 ± 0.074	0.827 ± 0.056	0.833 ± 0.053
	forest	0.937 ± 0.026	0.902 ± 0.030	0.885 ± 0.030	0.935 ± 0.029	0.908 ± 0.028
	water	0.870 ± 0.000	1.000 ± 0.168	0.950 ± 0.000	0.889 ± 0.104	0.958 ± 0.000
	other	0.968 ± 0.134	0.881 ± 0.090	0.906 ± 0.093	0.778 ± 0.099	0.891 ± 0.091

The results of the comparison between the oil palm area found in this study and the oil palm area statistics from the FAO and the MPOB show that the oil palm area extracted between 2000 and 2018 was consistent with the increasing trend of the FAO statistical area, but the extracted oil palm area was greater overall than the statistical area of the FAO (Figure 7).

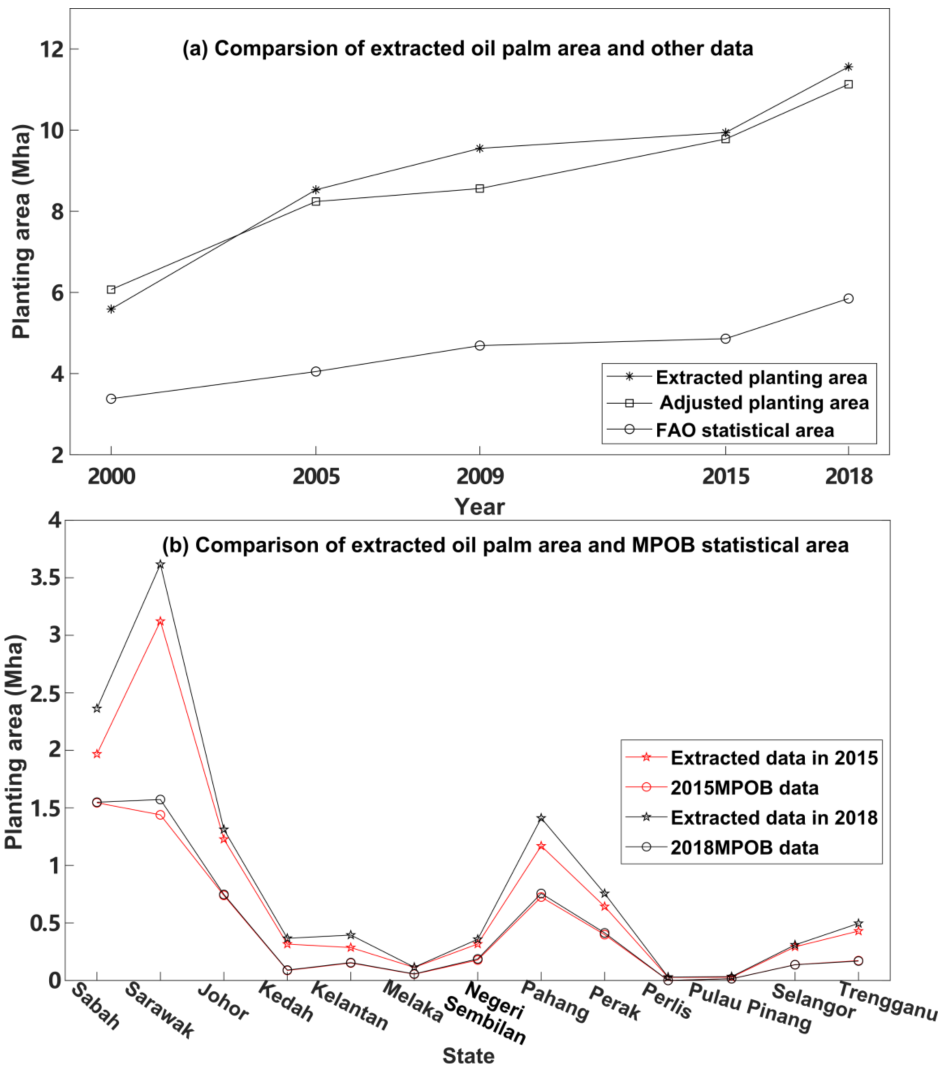

Figure 7. Comparison of the extracted oil palm area with the statistical areas of (**a**) the Food and Agriculture Organization (FAO) and (**b**) the Malaysia Palm Oil Board (MPOB).

The oil palm planting area extracted for the five periods was approximately 1.8 times that of the FAO statistical area (Figure 7a). The results of the comparison between the extracted 2015 and 2018 oil palm planting area data for each state with the data for each state published by MPOB were as follows. The average oil palm planting area extracted for each state was approximately 1.8 times that of the MPOB statistics (Figure 7b). The oil palm area of the state of Sarawak in 2015 was approximately 2.1 times that of the MPOB statistical area. In 2018, the extracted oil palm area in Sarawak was approximately 2.2 times that of the MPOB statistical area and higher than the state average.

We studied the Borneo deforestation and plantation data for 1973–2015 by Gaveau et al. [44], focusing on the expansion of East Malaysia oil palms between 2000 and 2015. Their results showed that the East Malaysia planting area was approximately 1.3 times that of the MPOB statistical area in 2015, which was 3.55 Mha. Cheng et al. [19] studied oil palm thematic mapping in Malaysia, and found that the oil palm planting area in Malaysia increased from 4 Mha in 2007 to 6.77 Mha in 2016, which was approximately 1.5 times that of the FAO statistic.

3.2. Shift in the Center of Gravity of Oil Palm Planting

According to the regional center of gravity statistics (Figure 8), the shift in the center of gravity of the West Malaysian oil palm plantation is not obvious. It moved slightly southward from 2000 to 2009, and the longest distance moved was only 10.75 km. The distribution then moved slightly northward, but the shifts were all located in the Temala district of Pahang. In general, the focus of oil palm planting in West Malaysia was relatively stable during the 18 years studied. The results show that the expansion rate of oil palm planting area in the states of West Malaysia remained stable.

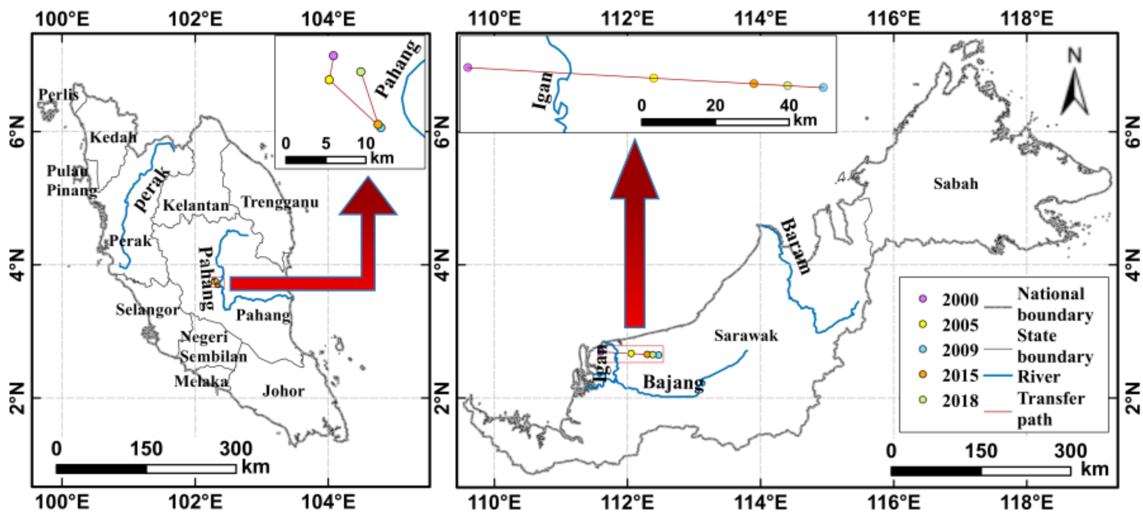

Figure 8. Oil palm planting center of gravity transfer path.

As shown in Figure 8, the focus of East Malaysia oil palm planting was located in the Igan River Basin in Sarawak in 2000. With the expansion of the oil palm planting area, the planting center of gravity continued to move to the eastern inland area. In 2009, the location of the center of gravity was 100 km from the center of gravity in 2000. After 2009, the planting center of the East Malaysia region moved around the Bajang River, indicating that the oil palm plantations gradually expanded from the coastal plains to the inland areas along both sides of the river. In the process of inland expansion, the elevation of the planting area gradually increased and formed two expansion modes: expansion along the river and expansion from the plain to the gently sloped area.

3.3. Relationship between Oil Palm Planted Area and Natural Environment, Socioeconomic, and Deforestation

Oil palm planting is mainly affected by factors such as annual average temperature, annual rainfall, and topography. Oil palms can grow in various tropical soils that are not suitable for growing other vegetation and require fewer soil nutrients and other resources [45]. Based on the influence of temperature and humidity during the growth of oil palms, this study selected representative altitude factors to study their effect on oil palm expansion. The oil palm classification results were analyzed at different altitudes by dividing the 30 m resolution DEM into different elevation zones. The results are shown below (Figure 9).

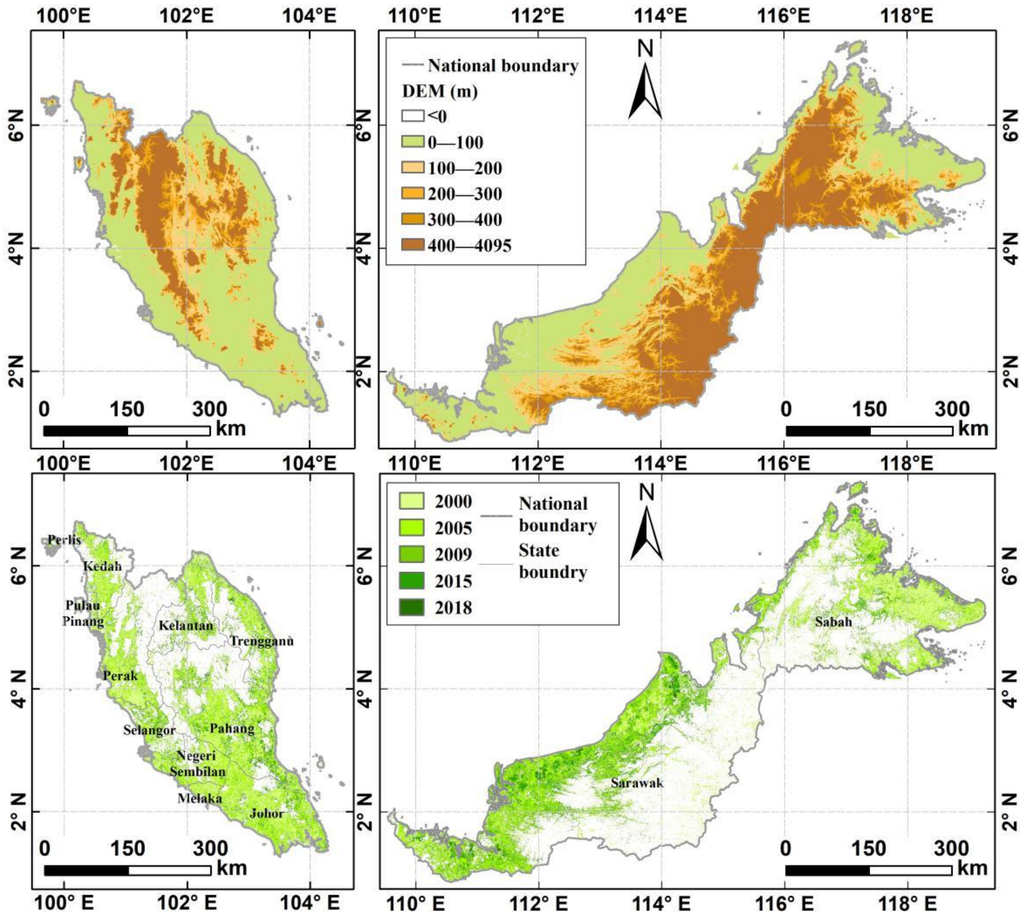

Figure 9. Spatial distribution of oil palms at different elevations. (**a**) DEM with different elevation zones and (**b**) spatial distribution of oil palms.

The planting area of oil palms is affected by various social factors, such as political, economic, and social development levels. The formulation of policies is generally influenced by economic factors, and the level of social development is also reflected in the economic situation. Therefore, this study selected the price of crude palm oil in 2000–2018 to represent the economic development of the oil palm industry and to reflect the impact of socioeconomic factors on the oil palm planting area.

As shown in Figure 10, during the study period, the prices experienced fluctuations, and the price of crude palm oil (CPO) from 2000 to 2018 rose from $240.12/ton to $538.21/ton. The price of CPO increased the most from 2000 to 2011 and reached the highest price ($776.04/ton) in 2011. Between 2011 and 2015, the price of crude palm oil gradually decreased until it reached the 2009 price. The price gradually recovered after 2015. In short, from 2000 to 2018, the price of CPO rose in fluctuations, and the oil palm plantation area also increased.

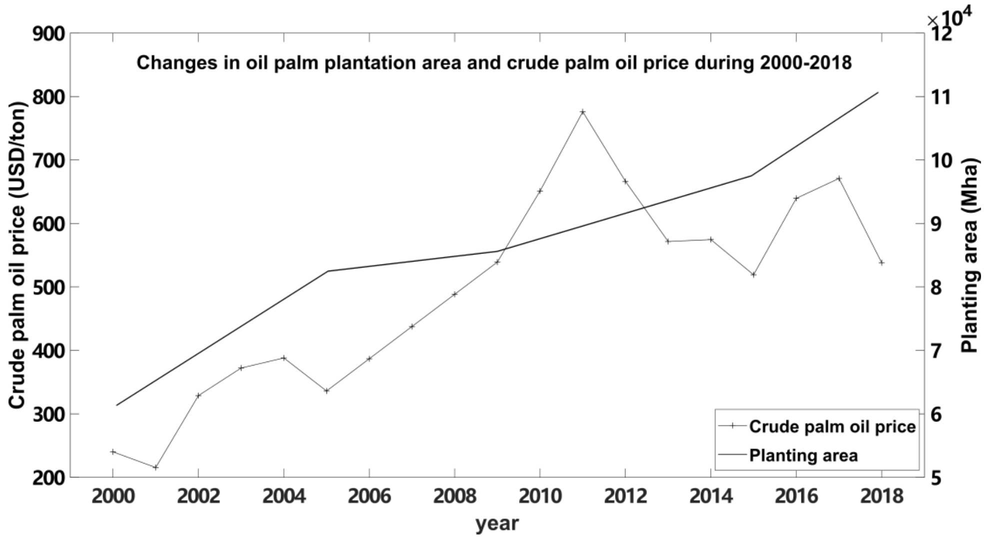

Figure 10. The changes in oil palm planting area and the price of crude palm oil.

By fitting the oil palm planting area of the five periods with the palm oil price for the current year (Figure 11), the previous year, and the previous two years, we found that the goodness of fit coefficients (R^2) of the curves were 0.82, 0.83, and 0.04, respectively.

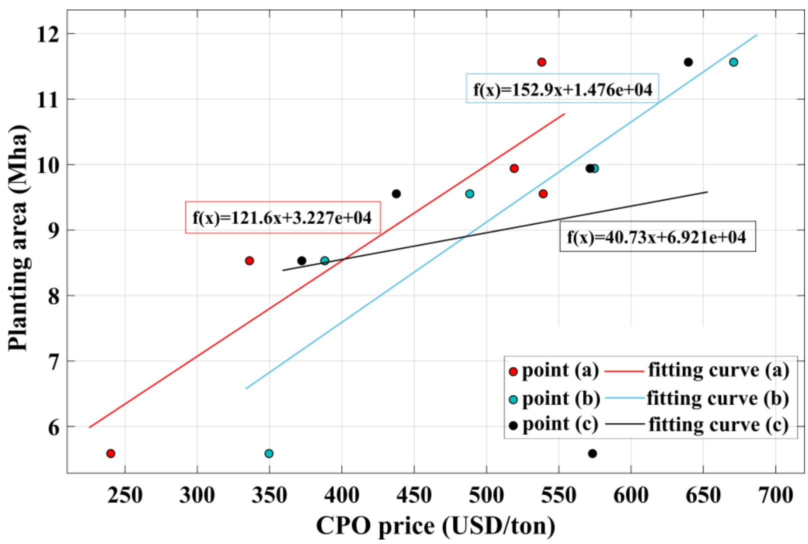

Figure 11. The curve fitting of the crude palm oil (CPO) price and oil palm planting area. Points refer the oil palm planting area vs. the price of CPO; fitting curve represents the fitting result of the oil palm planting area and the price of crude palm oil. (**a**)–(**c**) refer the current year, previous year, and previous two years, respectively.

Based on the comparison of the area of forest loss in Malaysia with the price change for crude palm oil in 2001–2017 (Figure 12), it was concluded that as the price of crude palm oil increased, the area of forest loss also showed an increasing trend. The trend of the two changes was fitted and analyzed; the goodness of fit coefficient (R^2) was 0.41, indicating a positive correlation.

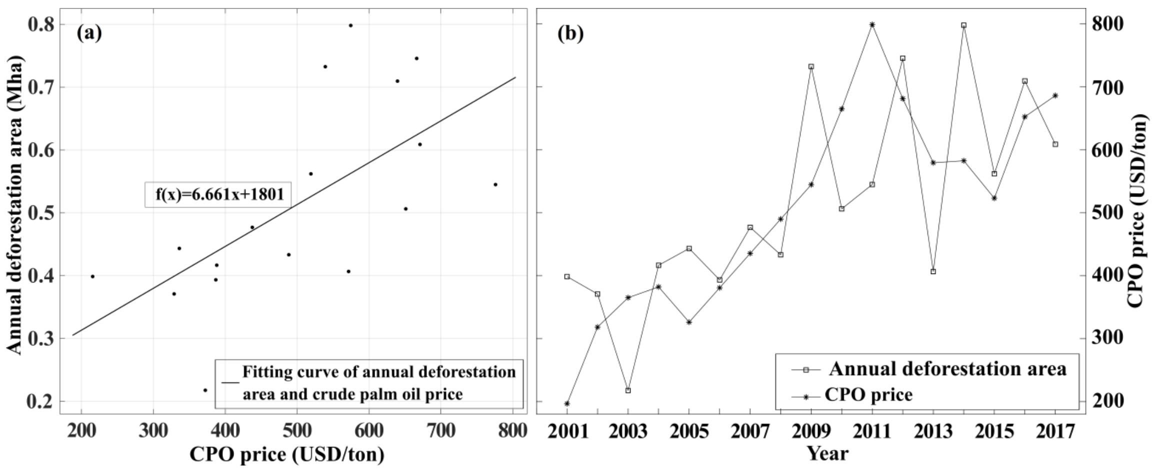

Figure 12. Relationship between forest loss area and CPO price in Malaysia during 2001–2017. (**a**) The fitting curve of the price of crude palm oil and the average annual deforestation area and (**b**) the curve of deforestation area and the price of CPO in 2001–2017.

4. Discussion

4.1. Oil Palm Planting Pattern

Based on our classification results and previous research on Malaysian oil palms [19], we speculated that the FAO may have underestimated the expansion of Malaysian oil palms since 2000, especially the expansion area of East Malaysia. From the classification results of oil palms from 2000 to 2018, the oil palm planting potential of East Malaysia was greater than that of West Malaysia. The main reason is that Sarawak and Sabah are sparsely populated and suitable for large-scale development of oil palm plantations. The large-scale oil palm forest in East Malaysia is conducive to the intensive production of palm oil and has gradually developed into two states with the largest oil palm planting areas in Malaysia.

From 2000 to 2018, the oil palm planting area in Malaysia increased, but the movement of the planting center of gravity was limited, and the center of gravity was always located near a river. East Malaysia's planting center of gravity was the farthest from the Bajang River in 2009, at approximately 40 km. The oil palm planting area of West Malaysia was largely filled in the expansion process. East Malaysia's oil palms are distributed near rivers, oil palm land cover ranges from plains to a gently sloped area; as such, the expansion rate of the East Malaysia planting area was higher than that of West Malaysia. The transfer distance of the oil palm planting center of gravity for East Malaysia was also longer than that of West Malaysia. In the process of oil palm expansion, three patterns were found: (i) from a fragmented pattern to a connected area, (ii) expansion along a river, and, and (iii) from a plain to a gently sloped area. West Malaysia was dominated by pattern (i), while East Malaysia was dominated by patterns (ii) and (iii).

In the early 20th century, the coastal plain was economically developed. Palm oil plants and wide roads were built in the plain, which were conducive to the cultivation of oil palms and the foreign trade of palm oil, resulting in a large number of oil palm plantations [46]. Due to the Malaysian government's encouragement to transform private plantations into oil palm plantations and to the introduction of multinational companies [25], there was a lack of planning and relative dispersion in the oil palm planting process. With the continuous expansion of the oil palm plantation, the expansion of the size of single plantations, and the increase in the area, different plantations were gradually merged, resulting in the change from a fragmented pattern to a connected area.

As the economy developed, the road gradually extended to the inland areas, and land use efficiency in coastal areas increased. The limited land and increased demand for palm oil caused oil palm plantations to gradually expand into inland areas. However, human activities are affected by the location of the river, and oil palms are inseparable from the influence of human activities during planting. The result was an expansion that extended along both sides of the river and upstream of the river during the inland expansion of oil palms.

Areas with higher altitudes and lower temperature are not conducive to the growth of oil palms. Therefore, as the altitude increased, the temperature and humidity, the oil palm planting area, and the expansion speed all gradually decreased. In this study, we found that oil palms were mainly planted at an altitude of 0–100 m, with a tendency to expand to 100–300 m, and an expansion pattern from a plain to a gently sloped area gradually formed.

4.2. Factors Affecting the Spatial-Temporal Variation of Oil Palm Planting in Malaysia

4.2.1. Natural Environment

Most of Malaysia has a tropical rainforest climate, and a small part has a tropical monsoon climate. The difference between the two climate types in terms of the annual average temperature and annual rainfall is not obvious. Therefore, this study mainly analyzed the natural factors affecting oil palm planting area in Malaysia from topographical aspects. First, the distribution of oil palms in the vertical zone of the mountain is affected by different factors, such as latitude, altitude, and illumination, and each factor has different effects on the growth of oil palms with increasing altitude. This effect is particularly evident in temperature and humidity. The temperature decreases by 0.6 °C per 100 m altitude gain, and the air humidity and soil moisture gradually increase to a certain level with increasing altitude, then gradually decrease [47]. Second, the oil palm fruit has a short shelf life, and the fruit needs to be delivered to the palm oil plant for processing within two days [48]. Therefore, the presence of flat and wide terrain that is convenient for transportation also has a great impact on the cultivation of oil palms.

As shown in Figure 9, the expansion area in West Malaysia was less than that in East Malaysia during 2000–2018. In West Malaysia, the expansion on the east coast of Pahang is clear, while the expansion in East Malaysia was mainly concentrated in the coastal plain of Sarawak. In 2000–2009, the oil palms of West Malaysia and East Malaysia were mainly distributed below 100 m. After 2009, the area planted above 100 m above sea level gradually expanded and was mainly concentrated in the central areas of Sabah, Negeri Sembilan, Kelantan, and East Malaysia. The economy of Negeri Sembilan was developed, the industry was in a state of agglomeration, and the economy was mainly based on secondary and tertiary industries [49]. Kelantan mainly produces rice, and large areas of rice fields occupy the vast plains [50]. In Sabah, oil palms were widely planted in the coastal plains between 2000 and 2009, and oil palm plantations in the plains were relatively saturated. As a result, these three states gradually expanded into high altitudes during the oil palm expansion process.

From the altitude of the oil palm expansion, it can be seen that more than 90% of the plantings were concentrated in areas below 100 m above sea level from 2000, and areas above 300 m above sea level were longer suitable for oil palm planting. Although our classification results show that oil palms are still planted in areas above 300 m above sea level, based on the growth environment of oil palms and visual verification combined with high-resolution images, we speculate that oil palms above 300 m were classified as our misclassifications. For example, the expansion of the planting area of oil palms in West Malaysia became slower and more saturated. The analysis found that the central mountain range of the central Malay Peninsula restricted the expansion of oil palms in this area. The oil palm planting in East Malaysia gradually extended from the coastal plain to the inland high-altitude area, and the expansion occurred faster than that in West Malaysia, despite being restricted by the central mountain.

In addition, we found that as altitude increased, human activity decreased, and sparse roads and inconvenient transportation in high-altitude areas hindered the timely delivery of oil palm fruit to palm oil plants for processing. Therefore, we speculated that the expansion of oil palms to high-altitude areas was not only affected by the natural environment, but also related to the traffic conditions in the area. For example, the altitude of the tropical rainforest in central East Malaysia gradually increased, and the conditions for the development of transportation were also limited. During the field trip, it was found that there are no suitable roads to transport goods extending into the central part of Kalimantan Island in East Malaysia, and there are many nature preserves in this area. Therefore, oil palms in the central part of East Malaysia are sparsely distributed.

4.2.2. Social Development Status

According to the relationship of the price of crude palm oil and oil palm planting area (Figures 10 and 11), there was a positive correlation between the area under oil palm cultivation and the price of crude palm oil—namely, the expansion of oil palm planting area was relatively accelerated as the rate of increase in crude palm oil prices increased. For example, the price of crude palm oil increased by $203.50/ton between 2005 and 2009, and the oil palm planting area increased by 11.98% during this period. In 2009–2015, the magnitude of the price change was larger, but in 2015, it was down by $20.04/ton compared with that of 2009. During 2009–2015, the oil palm planting area only increased by 4.06%, and the growth rate decreased by 7.92% compared to that of the previous period. Compared the increase in oil palm plantation area and the changes in prices of CPO, there may be a lag in changes in planted area.

Since it was affected by price changes, the oil palm area growth rate during 2000–2018 experienced corresponding fluctuations (Figure 10). From 2000 to 2005, the price increased, the oil palm planting area increased by 52.69%, and the average annual growth rate reached 8.83%. After 2005, to prevent the impact of excessive growth of oil palm planting area on other cropping industries and natural forests, Malaysia introduced a series of measures to regulate oil palm plantations [51]. This may be the main reason why the average annual growth rate decreased to 2.87% despite the continued price increases in 2005–2009. The price of crude palm oil fell slightly after volatility in 2009–2015. In response to the impact of the policies, the average annual growth rate fell to 0.66%. The price of crude palm oil remained stable in 2015–2018, and the average annual growth rate of oil palms gradually returned to approximately 5%.

4.2.3. Deforestation

According to satellite data and some previous research, the deforestation rate of tropical forests is related to the growth of urban populations, agricultural product prices, and the development of agricultural import and export trade [52]. Large-scale forest conversion in Malaysia and Indonesia is related to global demand for palm oil [53]. Therefore, there is an inseparable relationship between palm oil prices and deforestation, and since the introduction of oil palms in Malaysia in the 19th century, the area and distribution of tropical forests in Malaysia have changed dramatically [54].

Comparing the development of rubber trees deforestation, which have similar economic and ecological benefits to those of oil palms [55], it was found that the relationship between the price change for natural rubber and deforestation is similar to the relationship between the price change for crude palm oil and deforestation. This shows that there is a close relationship between the price of cash crops and the areas of cultivation deforestation [54]. As a typical tropical rainforest country, Malaysia's forest loss reached 8.77 Mha from 2000 to 2017, of which 68.17% was redeveloped into oil palm plantations. This indicates that the expansion of oil palms has a great impact on forest coverage.

In addition, the cultivation of oil palms causes excessive consumption of soil nutrients. In the process of increasing oil palm production, people use pesticides, herbicides, and fertilizers, resulting in the loss of habitats of animals and plants that originally grew in tropical rainforests, in addition to deforestation [56]. Especially in the Sabah and Sarawak regions, the replacement of tropical forests with oil palm plantations has led to the irreplaceable loss of biodiversity [57]. Although the RSPO has established policies related to oil palms, the European Union (EU), some environmental and biodiversity conservation organizations, etc., still hold opposing views on the deforestation effects of oil palm plantations. These challenges pose risks to the future development of oil palm plantations. As shown in Figure 12, the forest loss and oil palm expansion area in Malaysia were closely related to the price of palm oil. As the price of palm oil increased, the rate of expansion of oil palm plantations increased, and the rate of deforestation increased—these three factors form a cyclical relationship.

4.3. Limitations and Future Work

The results of this study can provide scientific support for future predictions of oil palm planting areas, estimations of palm oil production, calculations of oil palm age, oil palm planting areas, and price, and the determination of the relationship between oil palm plantations and deforestation. Nevertheless, there were some limitations to this research. First, only five years from 2000 to 2018 were selected to study the distribution of oil palms; thus, more frequent and earlier years could be added to improve the understanding of oil palm planting variation. Second, the accuracy of oil palm classification might be affected by cloud cover only using Landsat data. Therefore, microwave remote sensing data (e.g., Sentinel-1), which are not affected by cloud cover, might be taken into account in future research. Last, limited factors affecting the distribution of oil palm planting were analyzed in this study; more parameters could be used in future, such as distance to roads, labor, and gross domestic product (GDP).

5. Conclusions

This study used GEE to extract the oil palm planting distribution in Malaysia during five periods from 2000 to 2018 and analyzed the typical factors affecting the distribution of oil palm planting. The oil palm planting area in Malaysia increased from 6.06 in 2000 to 11.13 Mha in 2018—a total increase of 5.06 Mha with a growth rate of 83.50%. West Malaysia increased by 2.05 Mha, accounting for 33.83% of the increase, with a growth rate of 62.05%. East Malaysia increased by 3.01 Mha, accounting for 109.45% of the increase, with a growth rate of 136.14%. Furthermore, the FAO may have underestimated the growth status of oil palm planted area since 2000. In the process of expansion, oil palms may be affected by factors such as the natural conditions (represented by topography), human activities under the influence of natural factors (represented by traffic conditions), and social and economic development status (represented by the price of palm oil and deforestation).

Malaysia has the advantage of good natural conditions, such as temperature and humidity, for planting oil palms throughout the country. However, oil palms are still affected by factors such as topography, economic development, and environmental conditions during the expansion process. During the expansion process, oil palms show a trend of expanding from low-altitude to high-altitude areas and from coastal to inland areas. It was found that only approximately 10% of the oil palms were distributed between 100 and 300 m above sea level during the expansion process, and there were almost no oil palm planting areas above 300 m above sea level.

During the expansion of oil palms from coastal to inland areas, the direction of oil palm planting in West Malaysia and East Malaysia showed significant differences. The focus of planting in West Malaysia from 2000 to 2018 shifted toward the Temeru district of Pahang. However, from 2000 to 2009 in East Malaysia, the center of gravity of oil palm planting shifted 100 km inland from the coast, and in 2015 and 2018, it shifted to the coastal area, for a total of 10 km. The overall trend was to expand into inland areas.

With the increase in demand for palm oil, the price of crude palm oil has fluctuated and risen over the years, and the price in 2018 was 2.1 times that in 2000. Similar to the rising trend of crude palm oil prices, the area of oil palm plantation continued to rise from 2000 to 2018. Except to the price, the area of oil palm plantation was also closely related to deforestation. The deforestation area caused by oil palm planting in 2001–2017 reached 5.98 Mha, accounting for 68.17% of the total amount of deforestation.

Author Contributions: Conceptualization, Dongjie Fu; Data curation, Wenhui Li; Formal analysis, Wenhui Li; Funding acquisition, Fenzhen Su; Investigation, Wenhui Li and Yang Xiao; Methodology, Wenhui Li and Dongjie Fu; Project administration, Dongjie Fu and Fenzhen Su; Resources, Fenzhen Su; Validation, Wenhui Li; Writing—original draft, Wenhui Li; Writing—review and editing, Dongjie Fu and Yang Xiao. All authors have read and agreed to the published version of the manuscript.

Funding: The Strategic Priority Research Program of Chinese Academy of Sciences: XDA19060304 LZJTU EP: 201806.

Acknowledgments: This work was supported by the Strategic Priority Research Program of Chinese Academy of Sciences (Grant No. XDA19060304), Science and Technology Basic Resources Investigation Program of China (Grant No. 2017FY201401), LZJTU EP (Grant No. 201806), and the National Natural Science Foundation of China (Grant No. 41601460).

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Scanes, C.G. Human Activity and Habitat Loss: Destruction, Fragmentation, and Degradation. In *Animals and Human Society*; Academic Press: Milwaukee, WI, USA, 2018; pp. 451–482. Available online: https://www.sciencedirect.com/science/article/pii/B9780128052471000320?via%3Dihub (accessed on 1 April 2019).
2. FAO. FAOSTAT Database Collections. 2018. Available online: http://www.fao.org/faostat/en/#data/QC (accessed on 1 March 2019).
3. Sheil, D.; Casson, A.; Meijaard, E.; Van Noordwijk, M.; Gaskell, J.; Sunderland-Groves, J.; Wertz, K.; Kanninen, M. *The Impacts and Opportunities of Oil Palm in Southeast Asia: What Do We Know and What Do We Need to Know*; Center for International Forestry Research: Bogor, Indonesia, 2009; Volume 51, pp. 1–19. Available online: http://dlc.dlib.indiana.edu/dlc/handle/10535/5256 (accessed on 1 April 2019).
4. Lu, X.; Yangjie, L. Space-time Evolution and Forecast of the Oil Palm Production and Trade in the World. *World Geogr. Res.* **2012**, *21*, 70–76.
5. Zeng, Z.; Estes, L.; Ziegler, A.D.; Chen, A.; Searchinger, T.; Hua, F.; Guan, K.; Jintrawet, A.; Wood, E.F. Highland cropland expansion and forest loss in Southeast Asia in the twenty-first century. *Nat. Geosci.* **2018**, *11*, 556–562. [CrossRef]
6. Wicke, B.; Sikkema, R.; Dornburg, V.; Faaij, A. Exploring land use changes and the role of palm oil production in Indonesia and Malaysia. *Land Use Policy* **2011**, *28*, 193–206. [CrossRef]
7. Koh, L.P.; Wilcove, D.S. Is oil palm agriculture really destroying tropical biodiversity? *Conserv. Lett.* **2008**, *1*, 60–64. [CrossRef]
8. Wicke, B.; Dornburg, V.; Junginger, M.; Faaij, A. Different palm oil production systems for energy purposes and their greenhouse gas implications. *Biomass Bioenergy* **2008**, *32*, 1322–1337. [CrossRef]
9. Wakker, E.; Watch, S.; Rozario, J.D. *Greasy Palms: The Social and Ecological Impacts of Large-Scale Oil Palm Plantation Development in Southeast Asia*; AID Environment: Amsterdam, The Netherlands, 2004; p. 46. Available online: https://www.cabdirect.org/cabdirect/abstract/20056701996 (accessed on 1 March 2019).
10. Shafri, H.Z.M.; Ismail, M.H.; Razi, M.K.M.; Anuar, M.I.; Ahmad, A.R. Application of lidar and optical data for oil palm plantation management in Malaysia. In Proceedings of the Lidar Remote Sensing for Environmental Monitoring XIII, Kyoto, Japan, 1 November 2012; Volume 8526, p. 852608. [CrossRef]
11. Nooni, I.K.; Duker, A.A.; Van Duren, I.; Addae-Wireko, L.; Osei Jnr, E.M. Support vector machine to map oil palm in a heterogeneous environment. *Int. J. Remote Sens.* **2014**, *35*, 4778–4794. [CrossRef]
12. McMorrow, J. Linear regression modelling for the estimation of oil palm age from Landsat TM. *Int. J. Remote Sens.* **2010**, *22*, 2243–2264. [CrossRef]
13. Tan, K.P.; Kanniah, K.D.; Cracknell, A.P. Use of UK-DMC 2 and ALOS PALSAR for studying the age of oil palm trees in southern peninsular Malaysia. *Int. J. Remote Sens.* **2013**, *34*, 7424–7446. [CrossRef]
14. Asari, N.; Suratman, M.N.; Jaafar, J. Modelling and mapping of above ground biomass (AGB) of oil palm plantations in Malaysia using remotely-sensed data. *Int. J. Remote Sens.* **2017**, *38*, 4741–4764. [CrossRef]
15. Aziz, N.A.; Omar, W.; Kassim, R.; Kamarudin, N. Remote Sensing Measurement for Detection of Bagworm Infestation in Oil Palm Plantation. *MPOB Inf. Ser.* **2012**, *502*, 589–597.
16. Khamis, A.; Ismail, Z.; Haron, K.; Mohammed, A.T. Nonlinear Growth Models for Modeling Oil Palm Yield Growth. *J. Math. Stat.* **2005**, *1*, 225–232. [CrossRef]

17. Murphy, D.J. The future of oil palm as a major global crop: Opportunities and challenges. *J. Oil Palm Res.* **2014**, *26*, 1–24.
18. Basiron, Y. Palm oil production through sustainable plantations. *Eur. J. Lipid Sci. Technol.* **2007**, *109*, 289–295. [CrossRef]
19. Cheng, Y.; Yu, L.; Xu, Y.; Lu, H.; Cracknell, A.P.; Kanniah, K.; Gong, P. Mapping oil palm plantation expansion in Malaysia over the past decade (2007–2016) using ALOS-1/2 PALSAR-1/2 data. *Int. J. Remote Sens.* **2019**, *40*, 7389–7408. [CrossRef]
20. Hansen, M.C.; Potapov, P.V.; Moore, R.; Hancher, M.; Turubanova, S.; Tyukavina, A.; Thau, D.; Stehman, S.; Goetz, S.; Loveland, T.R. High-resolution global maps of 21st-century forest cover change. *Science* **2013**, *342*, 850–853. [CrossRef] [PubMed]
21. Gorelick, N.; Hancher, M.; Dixon, M.; Ilyushchenko, S.; Thau, D.; Moore, R. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sens. Environ.* **2017**, *202*, 18–27. [CrossRef]
22. Nemani, R.; Votava, P.; Michaelis, A.; Melton, F.; Milesi, C. Collaborative supercomputing for global change science. *Eos Trans. Am. Geophys. Union* **2011**, *92*, 109–110. [CrossRef]
23. Avijit, G. *The Physical Geography of Southeast Asia*; Oxford University Press: Oxford, UK, 2005.
24. Hock, S.S. *The Population of Peninsular Malaysia*; Institute of Southeast Asian Studies, Singapore University Press: Singapore, 2007; p. 342.
25. Köppen, W. The thermal zones of the Earth according to the duration of hot, moderate and cold periods and to the impact of heat on the organic world. *Meteorol. Z.* **2011**, *20*, 351–360. [CrossRef]
26. Cramb, R.A. Re-Inventing Dualism: Policy Narratives and Modes of Oil Palm Expansion in Sarawak, Malaysia. *J. Dev. Stud.* **2011**, *47*, 274–293. [CrossRef]
27. Moore, R.; Hansen, M. Google Earth Engine: A New Cloud-Computing Platform for Global-Scale Earth Observation Data and Analysis. Available online: http://adsabs.harvard.edu/abs/2011AGUFMIN43C..02M (accessed on 1 November 2018).
28. Bey, A.; Sánchez-Paus Díaz, A.; Maniatis, D.; Marchi, G.; Mollicone, D.; Ricci, S.; Bastin, J.-F.; Moore, R.; Federici, S.; Rezende, M. Collect earth: Land use and land cover assessment through augmented visual interpretation. *Remote Sens.* **2016**, *8*, 807. [CrossRef]
29. NASAJPL. NASA Shuttle Radar Topography Mission Global 1 arc second number [Dataset]. NASA EOSDIS Land Processes DAAC. 2013. Available online: https://lpdaac.usgs.gov/products/srtmgl1v003/ (accessed on 1 January 2019).
30. Farr, T.G.; Rosen, P.A.; Caro, E.; Crippen, R.; Duren, R.; Hensley, S.; Kobrick, M.; Paller, M.; Rodriguez, E.; Roth, L. The shuttle radar topography mission. *Rev. Geophys.* **2007**, *45*, RG2004. [CrossRef]
31. Olofsson, P.; Stehman, S.V.; Woodcock, C.E.; Sulla-Menashe, D.; Sibley, A.M.; Newell, J.D.; Friedl, M.A.; Herold, M. A global land-cover validation data set, part I: Fundamental design principles. *Int. J. Remote Sens.* **2012**, *33*, 5768–5788. [CrossRef]
32. Olofsson, P.; Foody, G.M.; Herold, M.; Stehman, S.V.; Woodcock, C.E.; Wulder, M.A. Good practices for estimating area and assessing accuracy of land change. *Remote Sens. Environ.* **2014**, *148*, 42–57. [CrossRef]
33. Harris, N.; Goldman, E.; Gibbes, S. Spatial Database of Planted Trees (SDPT) Version 1.0. Global Forest Watch: 2015. Available online: https://www.globalforestwatch.org/ (accessed on 1 March 2019).
34. Cheng, Y. Research on Monitoring Oil Palm Plantation Changes in Malaysia. Master's Thesis, Henan University, Kaifeng, China, 2017.
35. Lee, J.S.H.; Wich, S.; Widayati, A.; Koh, L.P. Detecting industrial oil palm plantations on Landsat images with Google Earth Engine. *Remote Sens. Appl. Soc. Environ.* **2016**, *4*, 219–224. [CrossRef]
36. Morel, A.C.; Fisher, J.B.; Malhi, Y. Evaluating the potential to monitor aboveground biomass in forest and oil palm in Sabah, Malaysia, for 2000–2008 with Landsat ETM+ and ALOS-PALSAR. *Int. J. Remote Sens.* **2012**, *33*, 3614–3639. [CrossRef]
37. Wahid, B.; Nordiana, A.; Tarmizi, A. Satellite mapping of oil palm land use. *MPOB Inf. Ser. MPOB TT* **2005**, *255*, 1511–7871.
38. Anselin, L. Local Indicators of Spatial Association-LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
39. Ying, L.; Chiwei, X.; Peng, L.; Luguang, J. Relationship of grain output and economic development from 1978 to 2013 in the major grain producing area of China. *Resour. Sci.* **2015**, *37*, 1891–1901.
40. Zhi, X.; Xianjin, H.; Hao, M.; Yang, Z. Spatial structure and evolution of tea production in China from 2009 to 2014. *Geogr. Res.* **2017**, *36*, 109–120.

41. Lishan, Q.; Yulan, W.; Jinguang, Z. Discussion on methods of curve fitting in experimental data processing. *J. Chengdu Univ. Technol. (Sci. Technol. Ed.)* **2004**, *31*, 91–95.
42. Lizhen, S. Research on the Principle and Its Application of Curve Fitting. Master's Thesis, Changsha University of Science and Technology, Changsha, China, 2015.
43. Jianhua, X. *Econometric Geography*; Higher Education Press: Beijing, China, 2006.
44. Gaveau, D.L.A.; Sheil, D.; Husnayaen; Salim, M.A.; Arjasakusuma, S.; Ancrenaz, M.; Pacheco, P.; Meijaard, E. Rapid conversions and avoided deforestation: Examining four decades of industrial plantation expansion in Borneo. *Sci. Rep.* **2016**, *6*. [CrossRef]
45. Pirker, J.; Mosnier, A.; Kraxner, F.; Havlík, P.; Obersteiner, M. What are the limits to oil palm expansion? *Glob. Environ. Chang.* **2016**, *40*, 73–81. [CrossRef]
46. Ordway, E.M.; Naylor, R.L.; Nkongho, R.N.; Lambin, E.F. Oil palm expansion and deforestation in Southwest Cameroon associated with proliferation of informal mills. *Nat. Commun.* **2019**, *10*. [CrossRef]
47. Guanghe, W.; Naiang, W.; Shuangxi, H.; Lianshu, T.; Jianming, Z. *Physical Geography*, 3rd ed.; Higher Education Press: Beijing, China, 2004.
48. Corley, R.H.V.; Tinker, P.B. *The Oil Palm*, 3th ed.; John Wiley & Sons Ltd: West Sussex, UK, 2015. [CrossRef]
49. Suprayitno, E.; Aslam, M.; Harun, A. Zakat and SDGs: Impact zakat on human development in the five states of Malaysia. *Int. J. Zakat.* **2017**, *2*, 61–69.
50. Saadatian, O.; Haw, L.C.; Mat, S.; Sopian, K. Perspective of sustainable development in Malaysia. *Int. J. Energy Environ.* **2012**, *6*, 260–267.
51. Hassan, P.; Jusop, S.; Ismail, R.; Aris, A.Z.; Panhwar, Q.A. Soil and Water Quality of an Acid Sulfate Soil Area in Kelantan Plains, Malaysia and its Effect on the Growth of Rice. *Asian J. Agric. Food Sci.* **2016**, *4*, 124–144.
52. DeFries, R.S.; Rudel, T.; Uriarte, M.; Hansen, M. Deforestation driven by urban population growth and agricultural trade in the twenty-first century. *Nat. Geosci.* **2010**, *3*, 178. [CrossRef]
53. McCarthy, J.F. Processes of inclusion and adverse incorporation: Oil palm and agrarian change in Sumatra, Indonesia. *J. Peasant. Stud.* **2010**, *37*, 821–850. [CrossRef]
54. Gibbs, H.K.; Ruesch, A.S.; Achard, F.; Clayton, M.K.; Holmgren, P.; Ramankutty, N.; Foley, J.A. Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. *Proc. Natl. Acad. Sci. USA* **2010**, *107*, 16732–16737. [CrossRef]
55. Grogan, K.; Pflugmacher, D.; Hostert, P.; Mertz, O.; Fensholt, R. Unravelling the link between global rubber price and tropical deforestation in Cambodia. *Nat. Plants* **2019**, *5*, 47–53. [CrossRef]
56. Fitzherbert, E.B.; Struebig, M.J.; Morel, A.; Danielsen, F.; Bruhl, C.A.; Donald, P.F.; Phalan, B. How will oil palm expansion affect biodiversity? *Trends Ecol. Evol.* **2008**, *23*, 538–545. [CrossRef]
57. Carlson, K.M.; Heilmayr, R.; Gibbs, H.K.; Noojipady, P.; Burns, D.N.; Morton, D.C.; Walker, N.F.; Paoli, G.D.; Kremen, C. Effect of oil palm sustainability certification on deforestation and fire in Indonesia. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 121–126. [CrossRef]