Manuscript Submitted	27.09.2021
Accepted	23.12.2021
Published	31.12.2021

Modeling Vegetation Index Changes in Taiwan from 2000 to 2020

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Abstract

Vegetation changes play an important roles in climate change. Information from patterns and trends of these factor reveals the state of the climate in a particular area and can be used to set up a proper monitoring program. This study aimed to investigate the annual seasonal patterns and trends of Normalized Difference Vegetation Index (NDVI) by sub-region and by region and to estimate NDVI increase per decade by region in Taiwan. NDVI time series data from 2000 to 2020 were downloaded from the MODIS website. The natural cubic spline method was used to model NDVI annual seasonal patterns and linear regression was used to investigate the trends. Furthermore, multivariate regression was applied to adjust spatial correlation and to estimate NDVI increases in each sub-region and region. The results show the NDVI increase in March of sub-region 1, 2, 3, 4, and 7 and sub-region 3 and 6 show two peaks in each year. The trends show sub-region 8 in region 1 had the highest mean NDVI which was above 0.8, while sub-region 2 had the lowest mean NDVI which was below 0.4. However, NDVI shows increasing trend in almost sub-region except sub-region 15, 22, 23, 27 and 36. In addition, the NDVI in all regions had increasing trends, except in the eastern Taiwan with stable trend. The average increased of NDVI was 0.01 per decade. In conclusion, vegetation index in Taiwan is considerably increasing while the causes of the increasing trends need to be examined in further studies.

Keywords: *Normalized difference vegetation index, cubic spline function, multivariate regression model*

1. Introduction

Normalized Difference Vegetation Index (NDVI) is a plant health index of greenness on land that can be used to analyze the density of vegetation on the ground. Vegetation is one significant to the energy balances on regional and global scales (Huryna & Pokorný, 2016). Furthermore, vegetation absorbs carbon dioxide during the day and releases oxygen to the ecosystem and for human beings. Alterations of vegetation can be assessed at various wavelengths in the visible and near infrared ranges, in which the flora reflects sunlight. Plant leaves tend to reflected a wide range of light wavelengths (Przyborski, 2019).

Vegetation changes not only interrupt carbon dioxide and water cycle, but also influence energy balance of the Earth’s surface, and affect LST changes (Liu et al., 2015). The alterations of vegetation on the ground from short to long term influence climate change at local and global scales (Bounoua, Collatz, Los, Sellers, Dazlich, Tucker & Randall, 2000). Increasing deforestation and human population affect the climate change especially reduction of greenness. Increasing NDVI has been reported in several parts of the world (Feehan, Harley & Van Minnen, 2009), while decreasing NDVI is also found (Liu et al., 2015, Zhang et al., 2013).

Most studies on changes of NDVI has considered large areas of mainland countries. However, there are few studies on NDVI changes from an urban heat island, of which Taiwan is one example. Its urbanization has increased rapidly since 1967. The expansion of population in Taiwan has influenced vegetation changes (Lai & Cheng, 2010). Furthermore, urban expansion is a significant factor in the evolution regionally and global and can influence the local climate. Information of vegetation changes is useful for setting up proper planning and management to prevent the adverse effects of climate change. Therefore, this study aimed to investigate NDVI seasonal patterns and trends and to estimate NDVI increase per decade by sub-region and region in Taiwan from 2000 to 2020.

2. Current study

2.1 Remote sensing

There were many previous studies attempting to investigate and monitor the complex processes of land degradation and vegetation variation made use of remote sensing methodologies to model some of the indicators that describe one or more aspects of land change. By relating these indicators to other climatic variables, such as surface temperature, rainfall, air temperature, elevation, land cover, and land use. They attempted to reveal geo and biophysical causes of observed vegetation greenness change (Fensholt et al., 2009; Herrmann et al., 2005). On a continental scale, Symeonakis & Drake (2003), they proposed a desertification monitoring system for sub-Saharan Africa that uses remote sensing data to model NDVI cover, while surface run-off and soil erosion were modeled based on spatial data from other sources. In addition, on a local scale, Omuto et al. (2011) developed a method for detecting the rate and extent of land degradation in Somalia. Furthermore, on a regional scale, in 2004 the European Space Agency (ESA) established the Desert Watch project to develop an information system based on remote sensing technology for monitoring land degradation trends over time (Eckert, 2015). MODIS remote sensing data was used in many previous studies to model NDVI variation (Gillespie et al., 2018; Eckert et al., 2015).

2.2 NDVI change

Many previous studies have explored and investigated the ways of detecting changes in vegetation index from local to global scales. Most of the studies containing and monitoring the vegetation and relating the amount of red and near-infrared reflected energy to the amount of the NDVI present on the ground surface (Huete et al., 1997). Vegetation indices are robust, empirical measures of vegetation activity at the ground surface. They are considered to improve the vegetation signal from measured spectral responses by merging two (or more) different wavebands, often the red (0.6e0.7 mm) and near-infrared wavelengths (0.7e1.1 mm). Furthermore, they offer reliable spatial and temporal comparisons of universal vegetation conditions and they are able to use and monitor the Earth's terrestrial photosynthetic vegetation activity (Solano et al., 2010). According to Eckert et al., 2015, they used NDVI time series data with 11 years data from 2001 to 2011 to investigate and detect land degradation and regeneration areas in Mongolia. They performed by using regression analysis, derived regression slope values, and generated a map of significant trends. They found that the areas of positive and negative land cover class change mostly matched with areas showing positive and negative NDVI trends, correspondingly. Moreover, NDVI data was applied to monitor temporal and spatial patterns from 2000 to 2016 within Santa Monica Mountains National Recreation Area and Channel Islands National Park of southern California. The study found that there was a significant decrease in NDVI especially during the summer (Gillespie et al., 2018).

3. Materials and Methods

3.1 Study area

The area of this study covers the whole Taiwan Island. Taiwan has rugged mountains running from the North to the South, with an area of 35,883 km^2 (World Population Review, 2019). In this analysis, Taiwan was separated into four regions following its original map that shows northern, central, eastern and southern regions. Each region consists of nine sub-regions giving 36 sub-regions in the whole analysis, as shown in Figure 1. The coordinates of each sub-region were retrieved from Google Earth program. To avoid overlap of sub-regions, we used the MODLAND tile calculator website to specify the latitude and longitude in order to get the tile horizontal and vertical coordinates, and line and sample numbers. The size of each sub-region is 7×7 km^2, which equals 49 pixels in a 1×1 km^2 grid. There were 1,764 pixels in the study area.

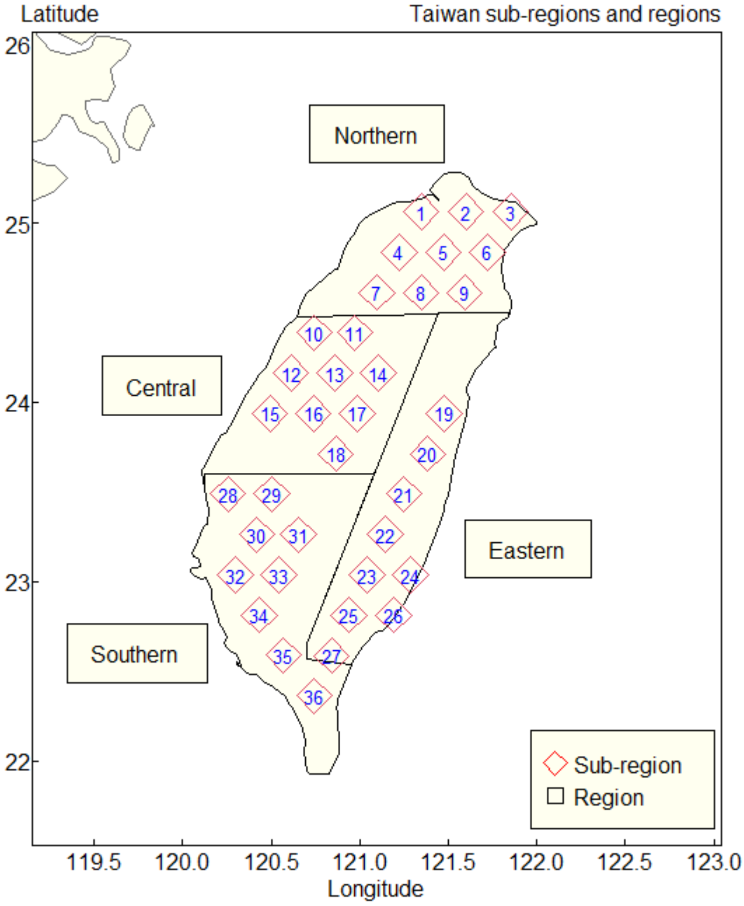

Figure 1: The map of Taiwan showing sub-regions and regions

Figure 1 shows the map of Taiwan with the sub-regions and regions. There are 36 sub-regions. Sub-regions 1-9 are in the northern, 10-18 are in the central, 19-27 are in the eastern and 28-36 are in the southern region.

3.2 Data source

The vegetation data were retrieved from the MODIS vegetation index website. The product name is Vegetation Indices (NDVI/EVI) (terra, 16 days, 250 m) (MOD13Q1). The NDVI data from March 2000 to February 2020 were downloaded. NDVI data were recorded every 16 days. There are approximately 23 observations in each year per grid cell. The total count of observations over 20 years is 441. The MODIS website provided the area of data format around the central point with 250 m^2 grid size in spatial resolution. The NDVI defines values from -1 to 1. The vegetation values nearby 0.6 to 1 indicate a forest. The values from 0.2 to 0.4 represent grassland and shrubs, while the values from 0 to 0.1 specify soil, concrete, rocks, snow land and barren land. The water areas are recorded as negative values (Weier & Herring, 2000).

3.3 Statistical analysis

Descriptive statistics were computed such as the average NDVI in each sub-region and region. Natural cubic spline model with specific boundary conditions to ensure smoothness over the period was used for NDVI seasonal patterns and trends in each sub-region. There were eight knots assigned in this model, which were on the days 10, 40, 80, 130, 240, 290, 330 and 360. Then, the seasonally adjusted NDVI were calculated by taking the original values and subtracting the predicted patterns, and adding the mean values to certify that average NDVI over the 20 years period are unchanged. Linear regression model was used to find the trends of seasonally adjusted of NDVI. Furthermore, to detect the temporal autocorrelation from the model, the first (AR1) and second (AR2) order auto-regressions were applied in Auto Regressive Integrated Moving Average (ARIMA) model. The trends of NDVI from ARIMA models of each sub-region were illustrated in time series plot. Then, NDVI increases by region were visualized on the Taiwan map to visualize the NDVI changes over 20 years. In addition, to eliminate spatial correlation, the average increases NDVI by region were estimated by using multivariate regression model. A forest plot was used to summarize the confidence interval of the increase of NDVI per decade. All statistical analyses and plots were done using the R program (R Core Team, 2020).

4. Theoretical Framework

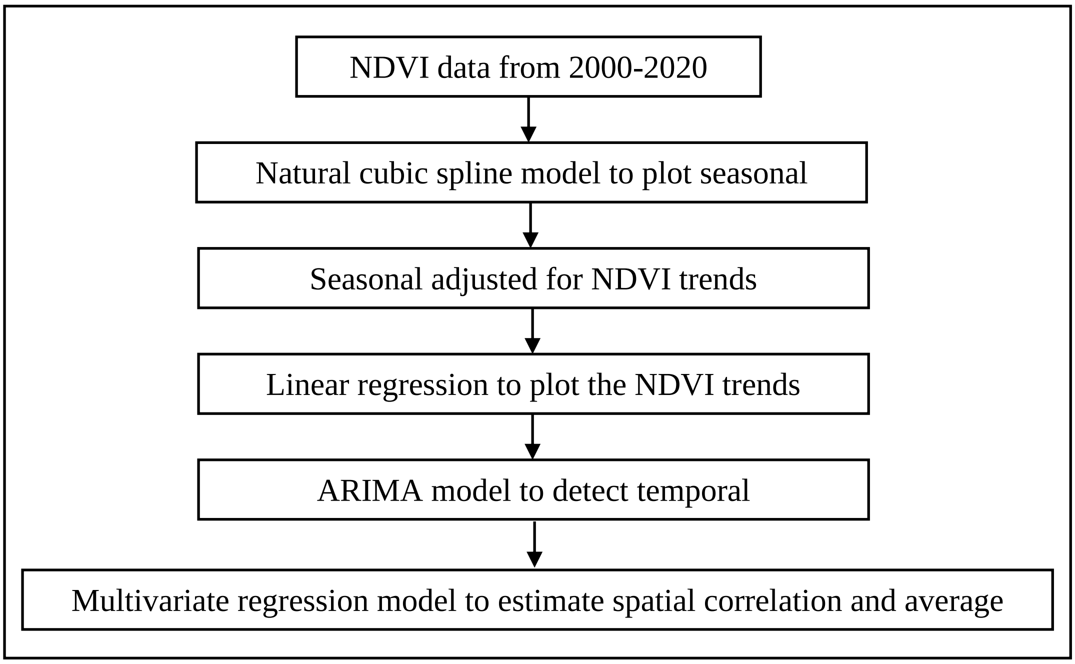

Figure 2: Theoretical framework of the study

5. Finding & Discussion

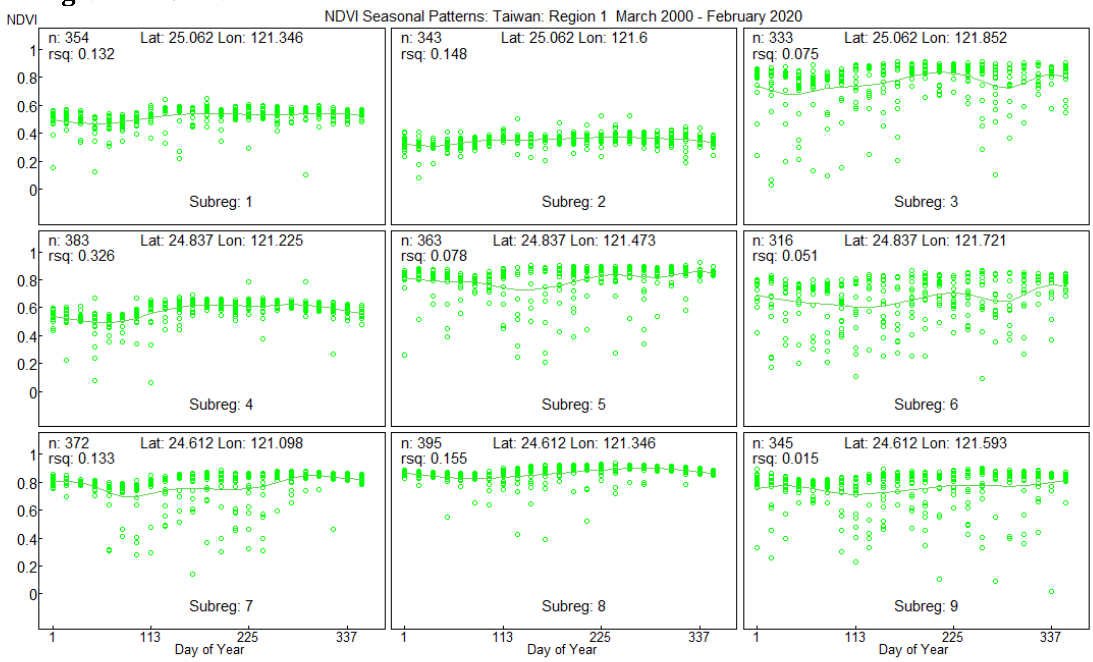

Figure 3: NDVI seasonal patterns in sub-regions of region 1 from 2000 to 2020

Figure 3 illustrates seasonal patterns fitted by natural cubic spline functions with eight knots. These nine plots represent NDVI seasonal patterns in region 1, which is in the north region of Taiwan used as an example to illustrate NDVI seasonal patterns. The Y axis represents the NDVI and the X axis shows the day of year. The green points denote average NDVI over 20 years. The result shows a steady increase of NDVI in March of sub-region 1, 2, 3, 4, and 7. Sub-region 3 and 6 had two peak of NDVI. The seasonal patterns for other regions showed broadly similar patterns for each year.

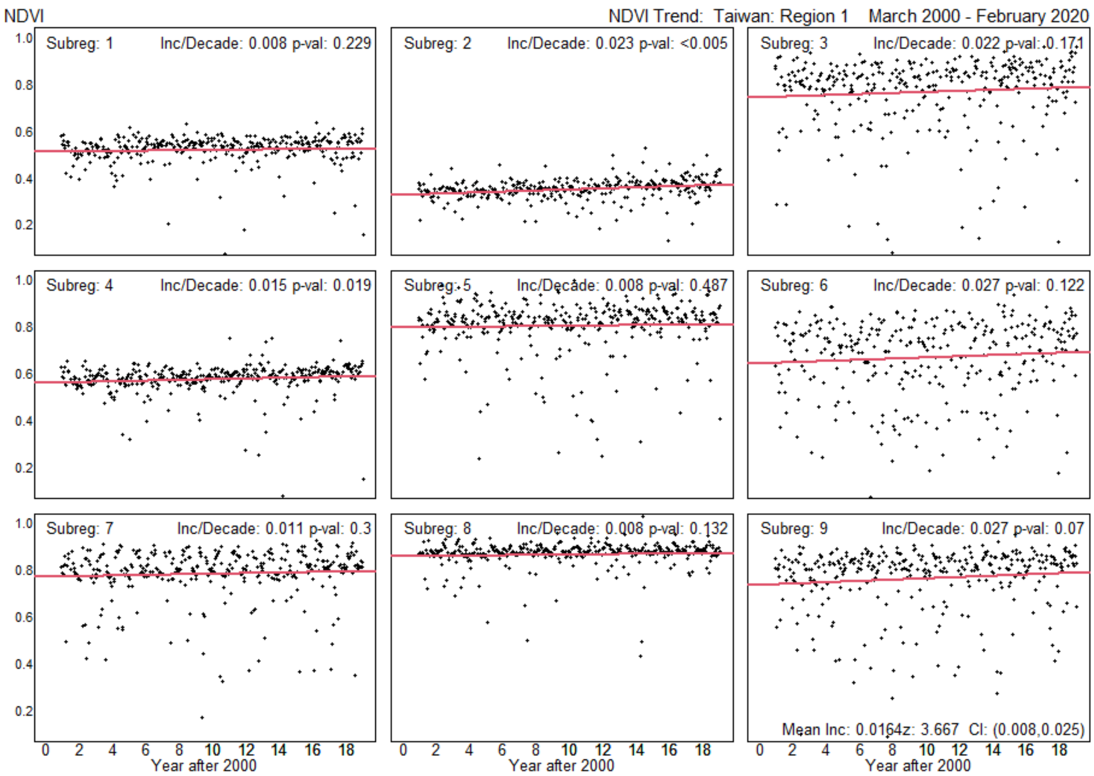

Figure 4: Time series trends for corresponding seasonally-adjusted NDVI in region 1 with 9 sub-regions

Figure 4 shows NDVI trends between years 2000 and 2020 from ARIMA models based on cubic spline function in north region. The results indicate different trends by sub-region. Sub-region 8 in region 1 had the highest mean NDVI which was above 0.8, while sub-region 2 had the lowest mean NDVI which was below 0.4. NDVI shows increasing trend in all sub-region except sub-region 15, 22, 23 and 27 as shows in table 1. The mean increases per decade and p-values from Figure 4 are summarized in Table 1. It was used to estimate NDVI increases by sub-region. Confidence interval (CI) and z-value in the bottom right panel of Figure 4 are summarized in Table 2 and these were used to estimate NDVI increase by region.

Table 1: The mean NDVI increase/decade with p-values for 36 sub-regions in Taiwan over 2000- 2020

Sub-region	**Increase**	**P-value**	**Sub-region**	**Increase**	**P-value**
1	0.008	0.229	19	0.023	0.019
2	0.023	0.005	20	0.024	0.054
3	0.022	0.171	21	0.012	0.448
4	0.015	0.019	22	-0.018	0.167
5	0.008	0.048	23	-0.007	0.613
6	0.027	0.012	24	0.017	0.020
7	0.011	0.300	25	0.002	0.801
8	0.008	0.132	26	0.027	0.005
9	0.027	0.070	27	-0.050	0.005
10	0.018	0.005	28	0.027	0.005
11	0.014	0.085	29	0.028	0.005
12	0.001	0.906	30	0.012	0.417
13	0.026	0.005	31	0.007	0.163
14	0.013	0.018	32	0.008	0.104
15	-0.001	0.806	33	0.030	0.005
16	0.021	0.005	34	0.029	0.005
17	0.021	0.005	35	0.007	0.065
18	0.030	0.005	36	-0.021	0.128

Table 2: NDVI increases with 95% CI (Confidence Interval) and z-values for each region over the years 2000 – 2020

Region	**Increase**	**95% CI**	**z-value**
Northern	0.016	0.008 - 0.025	3.667
Central	0.016	0.009 - 0.022	4.902
Eastern	0.004	-0.009 - 0.016	0.545
Southern	0.014	0.008 - 0.020	4.298
Average	0.012	0.004 - 0.021	

NDVI changes by sub-region and region

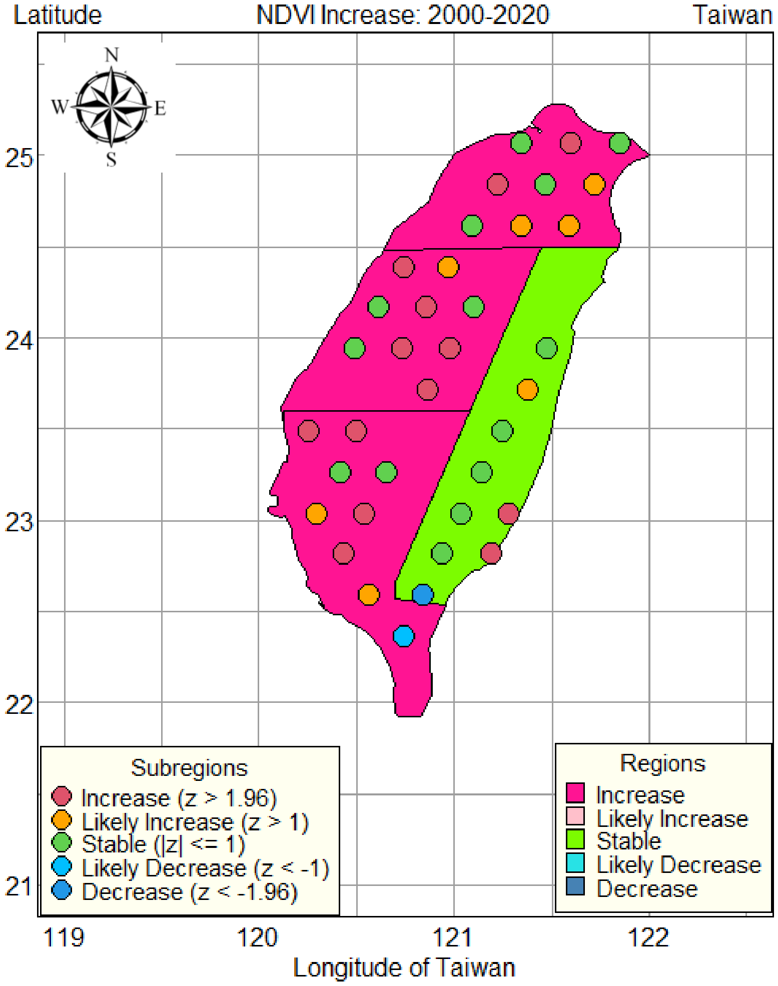

Figure 5: NDVI changes by sub-region and region in Taiwan from 2000 to 2020

Figure 5 illustrates the NDVI change of 36 sub-regions in four regions in Taiwan. The legends at the bottom right and left show vegetation index changes in different colors by sub-regions and by regions over 20 years. The increased and decreased values by sub-region were derived from mean increases per decade and the p-values in Table 1. If p-value <0.05 and increase >0, this is indicated as increase (red); if p-value <0.159 and increase >0 this is likely increase (orange); if p-value <0.159 and increase <0 this indicates likely decrease (light blue); and if p-value <0.05 and increase <0 this is decrease (blue); and other cases are stable (green). The increase and decrease by region and z-value were retrieved from Table 2. z-value is used to identify the increase and decrease levels. If the z-values of NDVI >1.96 there was increase (red); the values >1 to 1.96 mean likely increase (orange); values <=1 mean stable (green); values <-1 to -1.96 mean likely decrease (light blue); and values <-1.96 mean decrease (blue). The results show NDVI in all regions had increasing trends, except in the eastern Taiwan with stable trend.

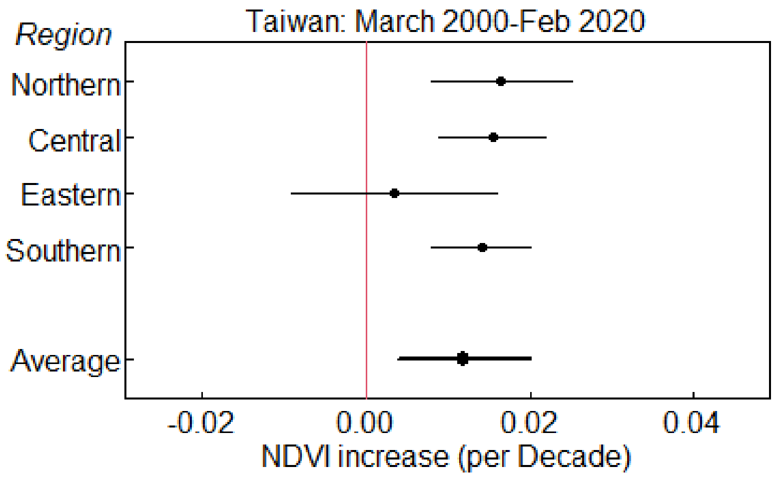

Figure 6: NDVI increases per decade from 2000 to 2020

Figure 6 presents forest plots to illustrate the confidence interval range of NDVI increases per decade. The Y axis shows the regions of Taiwan which consist of four regions: northern, central, eastern and southern. The X axis shows the increase in NDVI increase per decade. The plot illustrates the average increase of the NDVI was 0.01 per decade.

This study showed that cubic spline method with an appropriate number of knots and linear regression could successfully extract annual NDVI seasonal patterns and trends. In addition, by applying multivariate regression to adjust for spatial correlations and estimate NDVI increases by region was successful. Vegetation index has increased by 0.01 per decade. This study supports the finding from Tsai & Yang (2016) that there was a slightly increase in NDVI from 1982-2012 in Taiwan. The growing of vegetation because of rainfall was overwhelming, the plant roots produced oxygen for breathing that directly affect the absorption ability of nutrients and water of plant and also decreased light which negatively affect the photosynthesis of plant and stunted the growth of the vegetation (Ye et al., 2016; He et al., 2020).

Moreover, the finding from the current study is consistent with the results from the Global NDVI trends in the previous study of years 1982-2012. They indicated that NDVI had increased in several regions of the globe, including Western Europe, Southeastern United States, Amazonia, Sahel, India, Southeast parts of China, Tibet, India (Liu et al., 2015) and in Tibet Plateau of China between 2000 and 2009 (Zhang et al., 2013).

6. Conclusion and Future Recommendation

This study demonstrated an effective approach to time series data for modeling spatial and temporal changes NDVI by using MODIS time series data set. By using natural cubic spline model and multivariate regression model were successfully attract the seasonal patterns, trends and adjust special correlation in the time series. The study found that the highest mean increase trends of NDVI was in sub-region 8 of region 1 while the lowest mean increase trends was represent in sub-region 2. The NDVI in Taiwan have increased in the last two decades in all regions except in the eastern part of Taiwan which indicate stable.

However, the cause of the growing vegetation index is from agriculture. It is one of the main industries and a significant factor for increasing the greenness in Taiwan. The growing farming for instance rice, betel nuts, cocoa, chocolate, coffee, fruits, vegetables, tea and flowers has caused increases in vegetation index. The climate and spatial changes are terrible threats to ecosystems. Therefore, this is a signal to the Taiwanese policy makers to campaign against global warming. The causes of the increasing trends in these factor need to be investigated in further studies.

Acknowledgement
This paper is based on work supported by the Royal Golden Jubilee Ph.D. Scholarship under Thailand Science Research and Innovation (TSRI) and National Research Council of Thailand (NRCT) (Grant No. PHD/0205/2560). We acknowledge the Department of Research Methodology, Prince of Songkla University, Pattani campus and Department of Information Technology, Fatoni University for providing facilities for this study. We are grateful to Professor Don McNeil for his immense guidance during the study.

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