VEGETATION ANOMALIES DETECTED BY TIME-SERIES MODIS OBSERVATION

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ABSTRACT: Vegetation cover plays an important role in regulating the global climate by serving as the primary carbon pool for atmospheric carbon dioxide. Deforestation and forest degradation could pose a serious threat on the global emission of greenhouse gases, and this has been declared as the critical issue for United Nation's REDD programme. The study of vegetation dynamics and phenologic state, which traditionally relies on systematic field survey, could benefit from the long-term archive and analysis of remote sensed data. With more than ten years of observations, Moderate Resolution Imaging Spectroradiometer (MODIS) onboard Aqua and Terra satellites provides a reliable and consistent data source for monitoring of global biosphere. This study used time-series MODIS NDVI as the primary spectral indicator for monitoring of forest health and detection of vegetation anomaly. Based on ten-year dataset (2001-2010), NDVI reference and its annual variation were constructed for every 16-day data periods, while vegetation anomaly index (VAI) was measured as the NDVI difference (between reference and target images) normalized by the corresponding NDVI variation. With time-series analysis of VAI, we identified regions with abnormal spectral response, including land use changes (afforestation and agriculture expansion) and several major vegetation anomaly cases in Taiwan, with identified events such as drought spells in 2002, landslides following typhoon Morakot in 2009, and burn scars devastated by Alishan wildfire in 2009. Depending on the phenologic state and severity of these natural hazards, vegetation regrowth typically takes less than 1 month for the drought events, 2-4 months for the wildfire, and 3 months to over 1 year for landslides. Given cloud effect as the primary uncertainty sources for optical remote sensing, temporal slope of NDVI was used as the indicator for removal of false alarm (vegetation anomaly) as a result of atmospheric effect. Meanwhile, constraints for VAI as an anomaly indicator were discussed in this study.

1. INTRODUCTION

Satellite remote sensing has been used in forest studies as a method for monitoring the earth's terrestrial photosynthetic vegetation activity in support of phenologic and biophysical interpretations. It complements field survey and provides a reliable data source for derivation of forest structural parameters such as leaf area index (LAI), canopy height, above-ground biomass, and functioning measures such as primary productivity and evapotranspiration. Forest health managements, however, could also benefit from remotely sensed information covering vegetation mapping, invasive plant detection, fire fuel mapping, wildfire monitoring, post-fire burn area and severity mapping, insect infestation mapping, and canopy or foliar water stress. Studies have been conducted on a regional to global scale depending on the discipline in interest and data acquired in terms of their spatial, spectral, and temporal resolution.

With routine data acquisition (1-2 day global coverage) and calibration, MODIS provides a consistent and reliable data source for spatial and temporal comparisons of global vegetation conditions. The long-term archive and cost-effective data sources are also the prerequisite for anomaly studies if on a temporal basis. Among numerous vegetation indices, NDVI is the most commonly used for vegetation studies, and has a strong correlation to the presence and density of green vegetation. MODIS NDVI can be referred to as the continuity index for NOAA-AVHRR derived NDVI (1981-present), with enhanced spatial resolution for terrestrial application. It has been used extensively for detection of land cover/use change, green census, hazard monitoring, and forest health studies.

This study used MODIS NDVI as the potential indicator for monitoring of vegetation vigor and forest health in the forestland of Taiwan. Time-series archived MODIS data provide basis for operational monitoring of vegetation anomalies in support of the forestland management, while anomaly is defined as the presence of substantial departure of NDVI from its annual mean, when under similar phenologic state and environmental gradient. Specifically, the proposed method and data acquired will be explained first, followed by the results of detected island-wide anomalies (2001-2010). Subsequently, we focused on time-series NDVI response of vegetation with respect to several natural disturbances in the recent history of Taiwan.

2. METHODOLOGY

2.1 Normalized Difference Vegetation Index and MODIS VI Product

The study primarily used Terra MODIS vegetation index (MOD13Q1) product for construction of phenologic NDVI baseline and detection of vegetation anomaly. MOD13Q1 is calculated based on surface reflectance of the red and near infrared channels, which are corrected for molecular scattering, ozone absorption, aerosol optical thickness, and adjusted to nadir with use of a BRDF model, as input to the NDVI equations:

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \qquad \text{(eq.1)}$$

where
ρ_{NIR}: reflectance of the near infrared channel(841-876nm)
ρ_{Red}: reflectance of the red channel(620-670nm).

MOD13Q1 has 250m spatial resolution, and is derived at 16-day intervals with cloud screening procedure and maximum value compositing technique (MVC). Both the composite day and pixel reliability are also included in the data product. MVC characterize the highest NDVI observed in the data period. Since the influences of residual cloud and longer optical path length tend to lower NDVI, MVC could select the least atmospheric-contaminated and most near-nadir view observation within the compositing cycle. Such normalization procedure is critical for change detection and anomaly studies based on multi-temporal images.

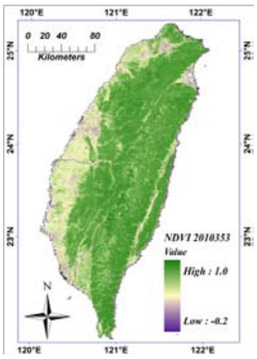

Figure 1 MOD13Q1 NDVI between 2010/12/19-2011/1/3

2.2 Vegetation Anomaly Index

NDVI is changing with different phenologic state and vegetation density. NDVI disparity in the spatial domain may simply indicate different vegetation composition or structure, and intra-annual (seasonal) difference may be a result of vegetation status between growing season and senescent month. Both should not be termed anomaly. Vegetation anomaly has been defined, specifically, as the significant change of vegetation vigor due to sporadic events, either naturally or anthropogenically-induced. Such change of vegetation vigor is expressed as the inter-annual difference of NDVI, with temporal (seasonal) and spatial coincidence.

With 23 data series for each year (16-day interval), and 10 years of data archive (2001-2010), a 2-D matrix of NDVI could be constructed in the temporal domain. NDVI reference and its annual variation were calculated for every 16-day data periods as:

$$NDVI\_ref_j = \frac{1}{n}\sum_{i=1}^{n} NDVI_{i,j} \qquad \text{(eq.2)}$$

$$NDVI\_std_j = \frac{1}{n-1}\sqrt{\sum_{i=1}^{n}(NDVI_{i,j} - NDVI\_ref_j)^2} \qquad \text{(eq.3)}$$

where
$NDVI_{ij}$: NDVI of the j_{th} data period in i_{th} year.

Vegetation anomaly index (VAI) was measured as the NDVI difference (between reference and target images) normalized by the annual variation of NDVI as:

$$VAI_{i,j} = \frac{NDVI_{i,j} - NDVI\_ref_j}{NDVI\_std_j} \quad \text{(eq.4)}$$

VAI can be seen as the signal to noise ratio, where NDVI difference is the signal we need for anomaly detection. Since NDVI is not a physically measurable parameter (e.g. LAI), but a relative description of the vegetation density, the normalization procedure gives VAI the statistical meaning required for anomaly detection. In the meantime, the normalization sheds its light not just on the decrease of false alarm, but on the increase of detection rate. For example, croplands used to present highly inter-annual NDVI variations due to slight shift of seasonal production cycle. Since such variation is normal, the potential large absolute difference of NDVI should not be termed anomaly. Thanks to the normalization process, this large difference could be balanced by its corresponding large variations. Another example is the application of VAI on the natural environment, which is characterized by stable seasonal cycle and smaller inter-annual NDVI variations. The slight decrease of NDVI triggered by some natural hazards (eg. drought, insect infestation), which shows no dramatic transform of local landscape, could not be easily seen if simply based on subtle NDVI difference. However, the normalization could enhance this contrast of anomaly signal and increase the detection rate.

2.3 Removal of False Alarm Due to Residual Clouds

In the MOD13Q1 VI data flow, variations associated with external influences (atmosphere, view and sun angles, clouds) have been accounted for in the upstream processing of reflectance products and in its MVC procedure. However, residual clouds and aerosol effects still pose major uncertainties for retrieved NDVI. A post-processing of cloud effects is necessary not just for the detection of vegetation anomaly, but for the decreasing of false alarm. Given the presence of residual clouds tends to lower NDVI and is usually randomly distributed, it shows no consistency in the temporal domain. A sudden drop and increase of NDVI could be identified in the time-series NDVI. We used temporal slope of NDVI as the potential indicator for search of cloud contaminated pixels (eq.5).

$$NDVI_{i,j}{}' = \frac{NDVI_{i,j+1} - NDVI_{i,j}}{t_{i,j+1} - t_{i,j}} \quad \text{(eq.5)}$$

where

$t_{i,j}$: composite date (Julian day) of the j_{th} data period in i_{th} year.

A temporal mask was applied to VAI with consideration of $NDVI_{i,j-1}'$ and $NDVI_{i,j}'$. The threshold was set at -0.006 and 0.006 respectively, based on the minimum/ maximum NDVI slope from the farm field. However, for implementation of this temporal mask, it will require 3 consecutive observations, which is challenging for some part of the lands and seasons. Therefore, a backup procedure is initiated, such that if neighbored period (j-1, j+1) presents no data (due to the presence of heavy cloud), the other period (j-2, j+2) would be used for calculation of this temporal slope. However, with prolonged period and potential NDVI variation, a more stringent threshold is applied (-0.004 and 0.004 respectively).

2.4 Detection of Vegetation Anomaly and Anomaly Event

For identification of anomaly event, which involves discrete discrimination between normal and abnormal situations, thresholds for its intensity (expressed as VAI) and span period need to be determined. However, different anomaly events may introduce different NDVI response. For example, drought may cause a prolonged anomaly period, but may not introduce significant NDVI difference when compared to anomaly triggered by floods. The determination of such threshold values is critical not just for the decrease of false alarm, but also to retain the detection rate of anomaly events. Therefore, multiple sets of thresholds have been determined for the identification process, such that

$$A_{i,j} = 1 \text{ if } VAI \le \rho_0,\ AE_{i,j} = 1 \text{ if } \sum_{j-m}^{j+m} A_{i,j} \ge k \quad \text{(eq.6)}$$

where

A: vegetation anomaly in the negative sense, and AE: identified anomaly event (Table 1).

The buffer interval between $2m+1$ and k is to consider the situation where no NDVI is retrieved within the span period, and significance of NDVI difference is derived based on the assumption of normal distribution among inter-annual NDVIs.

Table 1 threshold for vegetation anomaly and detection of anomaly event

scenario	ρ_0	significance of NDVI difference	m	k	comments on detected anomaly
1	-0.85	80.23%	3	5	long-lived, low intensity
2	-1.04	85.08%			moderate intensity
3	-1.65	95.05%	2	3	short-lived, high intensity

3. RESULTS AND DISCUSSIONS

3.1Annual Vegetation Anomalies

With time-series NDVI and VAI, vegetation anomalies for the negative departure ($VAI \leqq$-1.04) and positive departure ($VAI \geqq$1.04) from NDVI reference were illustrated in Fig. 2, where number of data periods showing anomalies were expressed in the spatial dimension. Since anomalies were detected independently in the spatial and intra-annual domain, aggregation of abnormal pixels along with prolonged period would enhance our confidence of detected anomalies, and these aggregated anomalies were even more likely to result from an identical or similar trigger(s). However, the identification of anomalies is straightforward, but the interpretation of it is even more involved. Several features could be utilized to enhance our awareness for the identified anomalies. We specifically chose two natural disturbances in the recent history as studied cases.

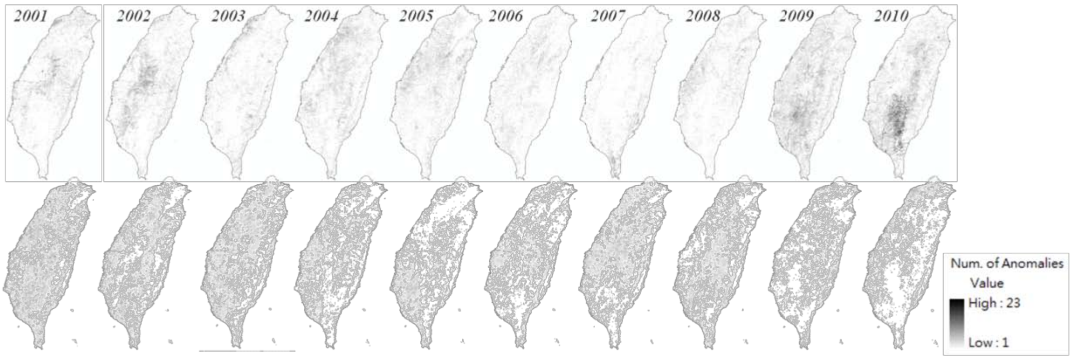

Figure 2 number of data periods presenting vegetation anomaly for the negative departure (upper: $VAI \leqq$-1.04) and positive departure (lower:$VAI \geqq$1.04) from 2001 to 2010

3.2 Case Studies of Anomaly Events

3.2.1 Drought in 2002

Drought is one of the major natural hazards in Taiwan. The severity could be explained by time-series mapping of its extent and corresponding duration. It is usually characterized by slight NDVI decrease and temporal slope, and such subtle NDVI difference could be enhanced by the normalization process in our VAI calculation. Fig. 3 shows time-series response of NDVI in 2002 along with 10-year average and ±1 standard deviation. The interval of identified anomaly event (scenario 1) is marked by the dash blue line in the upper part of the figure. Meanwhile, a typical example of residual cloud effect can be seen at DOY 321 data period, in which a sudden drop and increase of NDVI can be easily identified.

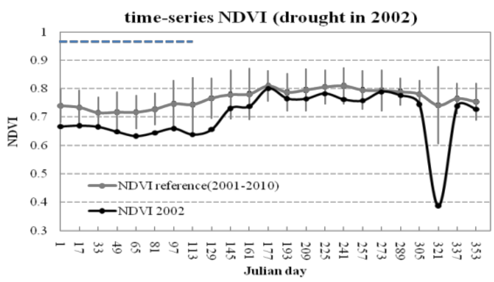

Figure 3 time-series NDVI in 2002 and 10-year average

The spatial extent of drought is coincident on the one side with isohyets at 250mm based on accumulated precipitation between 2001/10-2002/4 (Fig.4-5). The data were recorded and interpolated from measurements of more than 380 island-wide ground stations. The other side of VAI, which shows no correspondence with accumulated rainfall, is where the farmlands reside. Crop production in the western plain is typically supported by the irrigation system refilled from the reservoir in central mountain range. Therefore, unlike upland regions nearby, it shows no immediate response to the on-site precipitation shortage. Meanwhile, the cropland is characterized by higher NDVI variation in the seasonal domain, and this is depicted at Fig. 6 where intra-annual deviation were calculated based on 23 NDVI series in 2001.

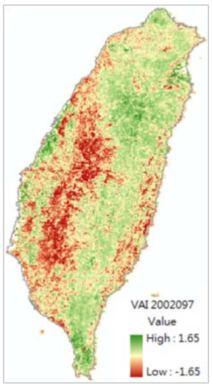

Figure 4 VAI of 2002097

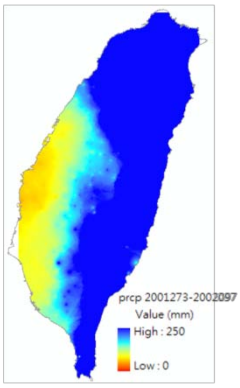

Figure 5 accumulated precipitation

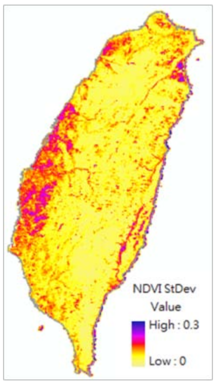

Figure 6 standard deviation of intra-annual NDVI

3.2.2 Alishan Wildfire in 2009

Compared to drought, wildfire is usually a short-lived disturbance. However, it has profound influence in regard to changes of vegetation density and composition. The conversion and evolution of the local landscape, typically is symbolized by significant changes of spectral signature and NDVI. This phenomenon has been illustrated in Fig. 7 for the fire incidence in Alishan region back on 2009/1/12 (DOY 17), where the duration of identified anomaly event (scenario 1 and 3) are signified by the dash blue and red lines. In this case, burn scars were mapped as 139.8 ha (based on post-fire aerial photos), and the spectral response (red and near infrared regions) took only about 3.5 months to recover, since post-fire vegetation regrowth was accelerated with the help from local officials. A cross-check of the incidence has also been done with MODIS fire alert derived from MOD14A2 thermal anomaly product (Fig.8).

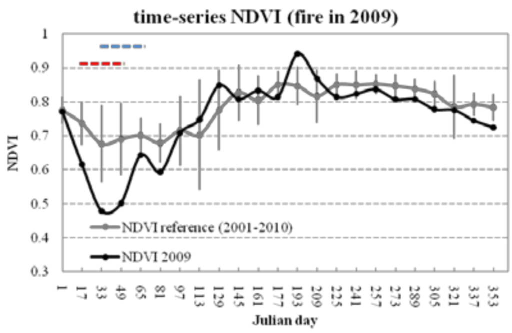

Figure 7 time-series NDVI in 2009 and 10-year average

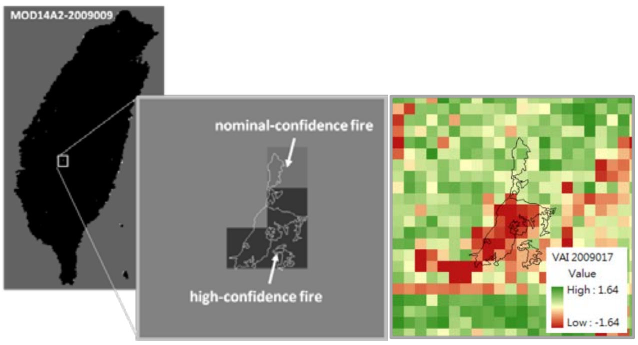

Figure 8 MOD14 thermal anomaly and VAI

3.3 Discussions

In this study, VAI has been developed to facilitate monitoring and interpretation of vegetation growth, drought, and wildfire dynamics. We specifically used NDVI, instead of physical characteristics, as our indicator for regular assessments of forest health. This is because NDVI is the direct spectral response of vegetation vigor, rather than derived parameters (eg. LAI, primary productivity) relied on physically/physiologically-based model or regression analysis. Even though the use of canopy parameter and its interpretation would be straightforward, the uncertainty from its derivation might further be introduced to the anomaly studies. In spite of this, some concerns of NDVI and MODIS MVC scheme associated with our anomaly studies still need to be clarified. For example, NDVI is confronted with saturation problems, whereby NDVI remains invariant to changes in the amount and condition of green biomass in densely vegetated canopies. This is attributed to the high sensitivity of NDVI to the chlorophyll absorption band. Such phenomenon may also imply that our derived VAI might not be sensitive enough to detect the subtle change of vegetation in dense forest. Fortunately, potential false alarm may also be reduced with the benefit from this radiometric buffer zone.

From remote sensing approach, the detection rate is associated with temporal and spatial resolution. Fine-scale or short-lived anomaly may not be detectable based on 16-day compositing and 250m NDVI dataset. MVC technique selects the maximum NDVI as the candidate for compositing cycle. However, the signal from short span event (eg. flood) is marked by low NDVI, and is more unlikely to be chosen as this candidate. Therefore, loss of alarm is to be expected, and this is compromised with the capability to detect anomalies on a nation-wide and 10-year scale.

What ecologists concern about is the change of vegetation condition in response to natural disturbance. We are more interested in the negative departure of NDVI from its average value. However, since VAI is just a statistical approach for identification of vegetation anomaly, we have to take into account the timing of this disturbance and the rehabilitation process following vegetation degradation. For example, some major disturbances (eg. landslide) may have a profound influence, or introduce permanent changes on the local landscape. It may take a much longer time to recover to its original condition (with respect to the statistical period). If such incidence occurs at the early stage of the statistical period, what we detect should be the positive departure of NDVI value, and the timing for occurrence of this incidence should be the end of this positive departure, rather than the starting point of vegetation anomaly. Therefore, the interpretation of detected anomaly is even more involved. Fortunately, it is not confronted with the confidence of our detected anomalies.

4. CONCLUSION

This study has developed an anomaly detection method to assess vegetation degradation and rehabilitation, and to incorporate climate and remote sensing parameters into evaluation of anomaly events. In our 2-dimensional NDVI matrix, the inter-annual domain has been used to construct NDVI reference, and vegetation anomaly index (VAI) was established to account for the significance of NDVI difference with its own statistical meaning. The normalization process in VAI derivation has special meanings not just for the decrease of false alarm, but for the increase of detection rate. Therefore, it could be used to detect slight anomaly cases marked by slight NDVI decrease (eg. drought), such will be challenging if simply based on visual interpretation or traditional classification procedure, since vegetation density and land cover pattern presents no significant changes. While in the intra-annual domain, time-series NDVIs were used for the removal of false alarm associated with residual cloud contamination, and for the identification of anomaly event. Given different anomaly events may introduce dissimilar NDVI response in terms of their change magnitude and span periods, multiple thresholds were set for the detection of various vegetation anomalies.

Atmospheric contamination is a major concern for optical remote sensing of land. In this anomaly study, we applied three steps for removal of atmosphere-induced false alarms. Cloud-flag embedded in MOD13Q1 data product offers the first screening of cloud/aerosol contaminated pixels, while residual clouds may still be present in the brink of these removed pixels. Given the presence of residual clouds tends to lower NDVI and is randomly occurred, it shows no consistency in the temporal domain. Temporal slope of NDVI was used as a robust indicator for search and removal of false alerts attributed to the cloud effects. Meanwhile, unlike cloud contamination, vegetation anomalies present spatially and temporally coincidence. Therefore, the threshold for their span periods gives another capability to reduce the chance for cloud alarm.

Long history of data archive is a prerequisite for ecosystem anomaly studies. Detection of vegetation anomalies and its dynamics depends on the reliability of reference dataset. Statistically, it implies that solid data archive is necessary for such application. The proposed VAI and anomaly detection method could apply to other long-standing dataset, such as NOAA-AVHRR and Landsat series data. It could not just increase the reliability of anomaly detection, but enrich the studies of forest dynamics back to 1980s.

5. ACKNOWLEDGEMENTS

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