A Novel Approach for Analysis of NDVI Change detection from Multiview Satellite Imagery Using Spatial Model

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--*ABSTRACT*--

NDVI in remote-sensing studies is a popular proxy for gross photosynthesis, and therefore, for vegetation productivity. A strength of NDVI is its normalization, which makes it relatively insensitive to radiometric attenuation present in multiple bands. Urbanization destroys the vegetation cover within the developed areas and at about 6–11 km distance around them. The studied urbanized areas have the NDVI values by 16 to 46 % lower than the corresponding areas at 20–40 km distance. The main weakness of NDVI is its inherent nonlinearity that leads to asymptotic saturation of NDVI over higher biomass conditions. As the acquisition date of the images did not coincide among years, which could have affected the NDVI ,check for temporal trends in the NDVI values that were not explained by variability of the climatic factors and the acquisition date of the images, we also incorporated the year of acquisition of the image as a covariate. This paper presents a Novel approach for analysis of NDVI change Detection from Multiview satellite imagery using spatial model.

KEYWORDS;- NDVI, Spatial Model, nDSM, IMD,

I. INTRODUCTION

Image processing is a vast field that cannot be covered in a single chapter. So why do we discuss image pre-processing in a book about computer vision.The reason is to advance the science of local and global feature description, as image pre-processing is typically ignored in discussions of feature description. Some general image processing topics are covered here in light of feature description, intended to illustrate rather than to proscribe, as applications and image data will guide the image pre-processing stage Changes in vegetation in the Mediterranean region have followed very different patterns. In general, vegetation growth tends to be favored by increased temperature in areas where water is not a limiting factor (Martínez-Villalta et al., 2008). Image pre-processing may have dramatic positive effects on the quality of feature extraction and the results of image analysis. Image pre-processing is analogous to the mathematical normalization of a data set, which is a common step in many feature descriptor methods. Various studies have identified changes in vegetation dynamics at continental, regional, and local scales in recent decades. Most changes have been caused by human activity, particularly deforestation and forest fires (Riaño et al., 2007), but land marginalization and rural abandonment have contributed to natural revegetation processes in some regions (VicenteSerrano et al., 2004). However, numerous reports have found a general increase in vegetation activity in various ecosystems of the world, suggesting that the principal causes of changes in vegetation dynamics are variations in precipitation and/or temperature (Delbart et al., 2008). In studies of smaller areas, similar NDVI trends in vegetation evolution have been observed, but human impact has been included among the explanations. The presence of a residual temporal trend in NDVI values following removal of climatic influences is usually considered to constitute evidence that other factors, such as human land use practices, are affecting vegetation activity.

II. LTERATURE SURVEY

The database comprised 28 images, 16 of which were from a summer time series and 12 from a spring time series. The two time series were used to identify possible differences in vegetation dynamics as a function of seasonal differences in vegetation activity, and to assess with more robustness any spatial and temporal patterns in vegetation activity. Semantic segmentation fuses input from orthorectified MSI and nDSM. Furthermore, we found the normalized difference vegetation index (NDVI) to be a useful inputas well. NDVI is derived directly from the red and near- IR bands of MSI as NDVI

Atmosphere reflectance data: $$NDVI = \frac{NIR - Red}{NIR+Red}$$

Where Red and NIR represent surface reflectances averaged over visible (λ~0.6μ m) and near infrared (NIR) (λ~0.8μm) regions of the spectrum, respectively.

Thus, the NDVI may not be suitable to infer vegetation fraction because of its nonlinearity and scale effects. We found that the scaled difference vegetation index (SDVI), a scale-invariant index based on linear spectral mixing of red and near-infrared reflectances, is a more suitable and robust approach for retrieval of vegetation fraction with remote sensing data, particularly over heterogeneous surfaces. Despite the need for integrating NDVI time series from different sensors, it is not well understood how phenological parameters and change trends derived from NDVI time series compare across sensors in different regions. Little information exists on which factors might lead to systematic biases, specifically in areas with low and strongly varying NDVI [52]. With the advent of new generations of sensors, [8], for example, pointed out that differences between AVHRR and MODIS time series in the spectral, radiometric, and spatial domain need to be better understood to meet the needs of long-term agricultural change research. The temporal series of NDVI for each land cover class was checked for temporal trends using the Spearman's correlation test against time. This enabled analysis of the vegetation dynamics in terms of increased (positive correlation) and decreased activity (negative correlation). The significance of the trends was checked using the p value associated with the Spearman's rho statistic. This involved use of a digital terrain model (DTM) with a spatial resolution of 20 m to derive the slope gradient (m m-1), as some studies have shown that this can be a major factor explaining rates of vegetation recovery (Pueyo and Beguería 2007). We also derived a model of the incoming solar radiation (MJ m-2 day-1) to assess topographic control of the energy balance, using an algorithm that includes the effect of terrain complexity (shadowing and reflection) and the daily solar position (Pons and Ninyerola, 2008).For the study sites located in tropical West Africa and temperate France, a strong correlation was found between the two types of NDVI computed and they concluded that NDVI derived from the coarse spatial resolution sensor data can be used in lieu of NDVI integrated from fine spatial resolution without introducing significant errors.

III. PROPOSED METHOD:

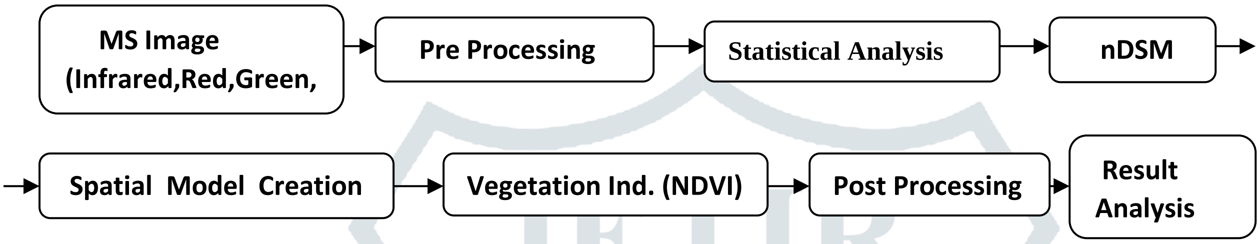
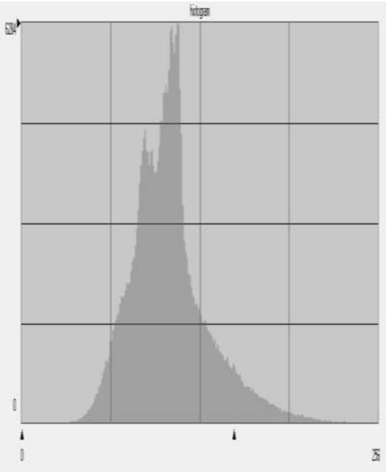



fig 1. Original Image

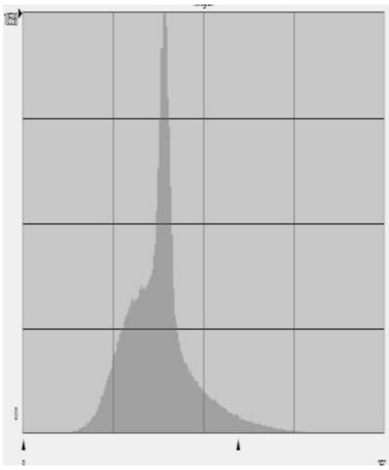

fig 2.After Image Sharpening

Table:1

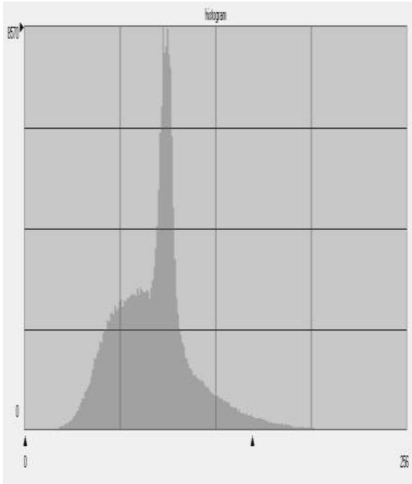
	Statistical Information	Layer_1	Layer_2	Layer_3
1.	Min	1	1	1
2.	Max	255	255	255
3.	Mean	106.581	97.387	87.781
4.	Median	104	97	90
5.	Mode	111	100	92
6.	Std. Dev.	29.617	26.314	28.190



3.1 Histogram for Layer_1



3.2 Histogram for Layer_2



3.3 Histogram for Layer_2

fig 4. Virtual GIS of Object

Table 2: Virtual GIS Data

Layer	Band	Struct_efio_FdRec PIXEL	LUT Value	Histogram
1.		109.000	89.000	5315.000
2.		119.000	124.000	1358.000
3.		175.000	65.000	3023.000

IV. SPATIAL MAODEL

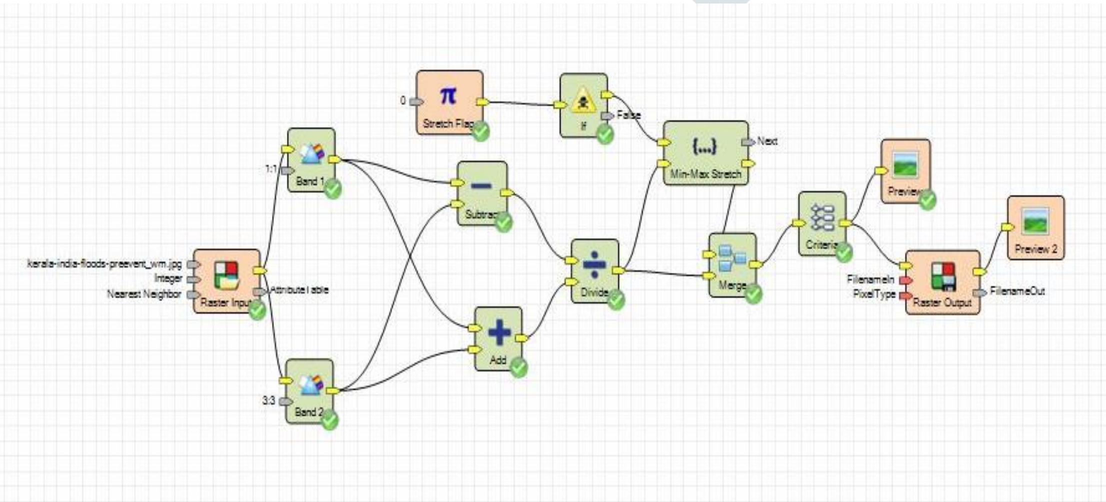
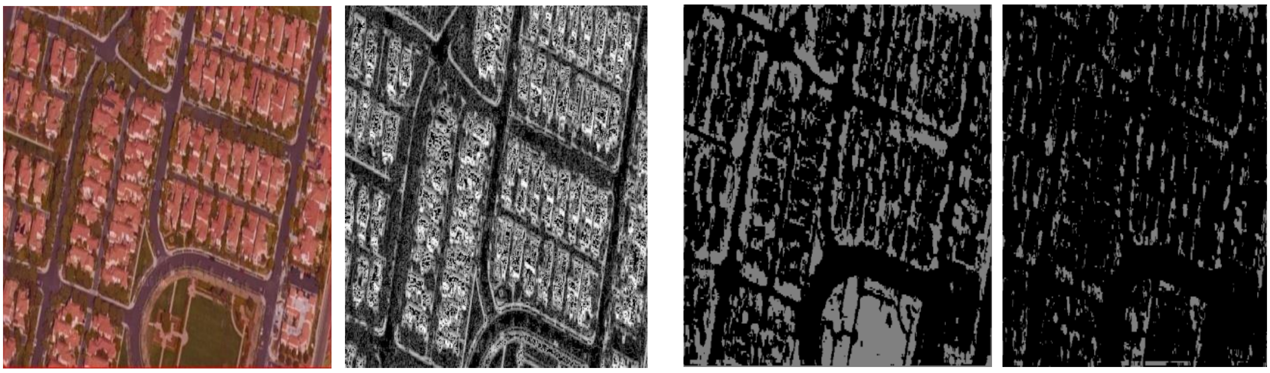
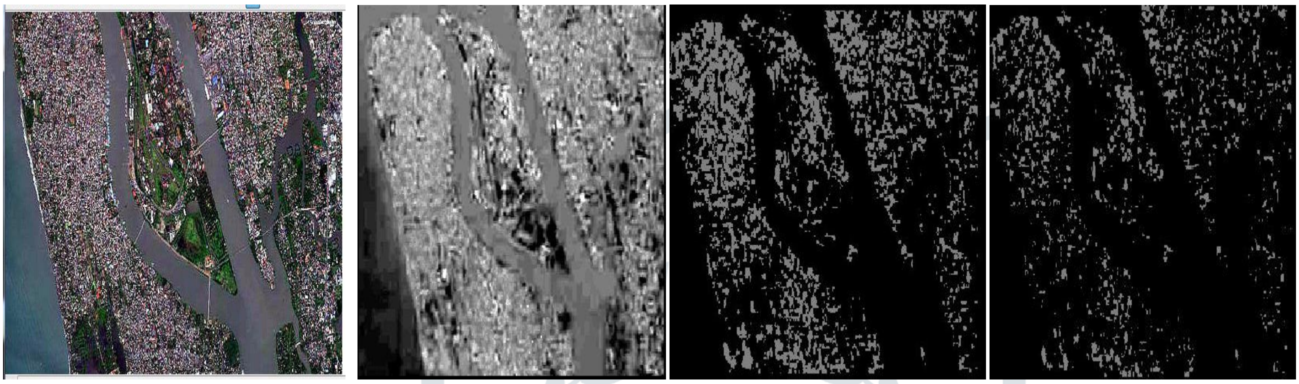


Fig 5 Spatial Model For NDVI

V. RESULTS AND DISCUSSION



(a) Original Image (b) *DEM Image* **(c) Higher Indexed Vegetation** **(d) Lower Indexed Vegetation**



(a) ***Original Image*** **(b)** ***DEM Image*** **(c) Higher Indexed Vegetation** **(d) Lower Indexed Vegetation**

Table 3: Result Analysis

	Case 1	Case 2
Threshold (dark)	10	35
Threshold (bright)	255	255
a. GIS Vegetation (pixel)	4324	4324
b. Extracted Vegetation segment (pixel)	3561	3120
c. Correctly extracted GIS Vegetation (pixel)	3425	2669
d. Correctly extracted Vegetation segment (pixel)	3824	3651
Correctness	13.5 %	14.3%
Completeness	58.2%	63.3%

VI. CONCLUSION

Temporal NDVI trends were identified for each land cover class using multivariate regression analysis, which incorporated the time evolution of climatic factors (precipitation, and minimum and maximum temperature). Seasonal differences were expected in the spatial pattern of vegetation activity and vegetation recovery processes, as a consequence of the climatic seasonality of the region and the large differences in water availability between spring and summer (vegetation in the latter season is commonly affected by a high level of water stress). Assignment to class based on the most representative category, by surface area, in a 30 m pixel size could introduce some errors, but it was necessary to guarantee an effective spatial comparison between the NDVI dataset and categorical information. Moreover, the results were spatially consistent, and clear NDVI patterns that coincided with the spatial distribution of land use and land cover were evident. In summary, this study demonstrated that, in a representative mountainous area of the central Spanish Pyrenees, there has been a significant increase in vegetation activity in the last 24 years, which is largely explained by an increase in the minimum temperature.

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