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Stress mapping of Sundarban mangroves with Sentinel-2 images using Discriminant Normalised Vegetation Index (DNVI) and Fuzzy classification technique

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Abstract: The present work reports stress mapping of Sundarban mangroves implementing fuzzy classification technique to Sentinel-2 data. A recently developed health index for mangroves, namely Discriminant Normalised Vegetation Index (DNVI) was used as a tool for extracting the signatures of stressed and healthy vegetation from Sentinel-2 image along with field survey data. Fuzzy classification of stress and health conditions allowed the pixels to acquire partial membership of different classes. The partitioning of the classes was resolved by convolving the fuzzy classes based on DNVI and normalised difference vegetation index (NDVI). A saturating tendency of NDVI was noted when compared to DNVI and consequently the later was assigned the first layer for determining fuzzy convolution weightage. The precise result in the form of micro-level stress map indicates that the stress is a probable function of local geomorphology, topography and physiography. This method appropriately represents the fuzzy pattern of natural forest cover rather than that obtained with fixed algorithm based hard classification methods. The approach also highlights the need of mapping the stress of different assemblages discretely instead of a single health index. Similar index value for different mangroves may not represent similar health conditions for all of them because of their different physiology.

Key words: Stress mapping, DNVI, Mangroves, Sentinel-2, Fuzzy classification.

1. Introduction

Paradigm changes in the global climate result in increasing global temperature, changing precipitation pattern, sea level rise, prolonged droughts, heat waves and continued intensification of storm events (Hansen et al., 1988; Knutson et al., 2010; Allen et al., 2010, Trenberth, 2011; Hoffman et al., 2017; Nerem et al., 2018; Mal et al., 2018). Mitigation of such a state and its further abatement requires assessment of the basic elements of the ecosystems. Forests, in addition to water bodies, atmospheric dynamics and human activities function as such elements and are the most important terrestrial ecosystems globally affected by anthropogenic activities (Prăvălie, 2018).

Mangrove forests are categorically evergreen sturdy vegetation thriving in intertidal regions of tropics and sub-tropics. They support coastal communities by means of invaluable ecosystem services (Himes-Cornell, 2018). Almost 40% of world's population is living within 150 km of coastlines (Cohen et al., 1997) and the consequent pressure has incurred a massive loss to the mangrove area (Polidoro et al., 2010). Most of the residents of tropical and subtropical coasts greatly depend on mangrove ecosystems for their livelihood and sustenance, either directly or indirectly. Apart from that, these forests provide a protective buffer to the coasts against natural calamities like cyclones and storm surges. Presently these forests are spatially dwindling with '*cryptic ecological degradation*' (Dahdouh-Guebas et al., 2005). Monitoring the mangroves has always been a challenge owing to their complex structure, muddy substrate and tough accessibility. Moreover, these vast ecosystems are sensitive to disturbances and may take over a decade to restore (Smith et al., 1994). In order to analyse such ecosystems and to address their present-day status, researchers use remote sensing as a synoptic tool.

Remote sensing of mangroves requires substantial inputs due to differential resolutions of the satellite data. Literature survey illustrates the use of vegetation indices developed at various times for the interpretation of biophysical parameters using optical remote sensing (Kuenzer et al., 2011) in mangroves. Almost all of the established vegetation indices use spectral response at red and near infrared wavelengths (Bannari et al., 1995; Broge and Leblanc, 2001; Adam et al., 2010) as they are relatable to the leaf pigments and canopy structure. The knowledge of the stress on mangroves induced by geomorphology and other associated parameters is essential for understanding the forest dynamics. To date there has been little work on mangrove stress mapping using remote sensing.

Chellamani et al. (2014) used NDVI for assessment of health status of mangroves in India from SPOT-VGT sensor and categorised mangroves into poor, moderate, health and very healthy. However, it was not stated as to how NDVI can directly portray the health, except for referring to previous studies where NDVI was reported (Tucker, 1979) to be sensitive to green leaf biomass. The health of mangroves cannot be depicted solely based on their canopy density or chlorophyll concentration because different mangrove species have their respective compositional construct and morphology. Domination of a single species covering top-canopies and association with other species standing as under-canopies results in the admixture of canopy reflectance and makes the mapping of the absolute composition challenging. However, active remote sensing is capable of interpreting subsurface organisation of flora (Kuenzer et al., 2011). In the case of analysis of spaceborne optical image, the combination of different spectra in a moderate resolution image is perplexed with background responses raising the need of fine resolution data. The phenology of the mangroves indicates their behaviour like evergreen forests as they continuously shed the senescent leaves to be replaced by the young ones.

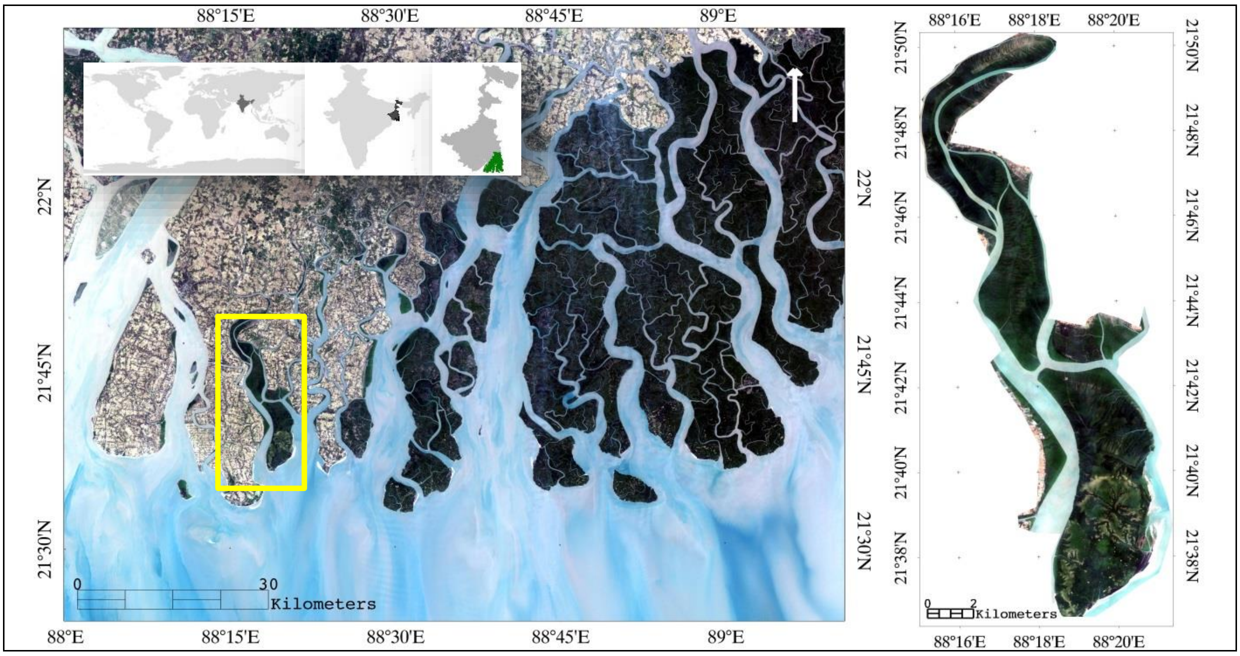

Figure 1: Map showing Indian part of Sundarban (left) and Lothian island with adjoining islands of the study area. Inset maps not to scale.

Stressed mangroves shed leaves resulting into gradual reduction of canopy cover. Various environmental stressors could also lead to reduction of stem density and overall basal area. The dwarfing is another effect leading to morphological changes including branching pattern, wood density and canopy height. Apart from that, mangroves located much inland and receiving infrequent tidal inundation also suffer from stresses (Saenger 2002). Therefore, health mapping of mangroves must account for various parameters like leaf density, chlorophyll concentration, water content, cellulose-lignin content, and nutrients; and most importantly the species or cohort specific assessment owing to difference in dissimilar and congeneric species. All these parameters are comprehensively not relatable to indices solely based on red and near infrared reflectance, hence require the integration of SWIR responses. The stress indicating index used for mangrove assessment, termed as DNVI was developed recently with Sentinel-2 data (Manna and Raychaudhuri 2018). Under circumstances like hypersaline substratum and inadequate influx of tidal and fresh water combined with sediment deposition, the mangroves stands gradually transform into saline blanks with population of dwarf and stunted individuals. Such regions also illustrate some rank higher than absolute zero on NDVI scale. DNVI on the other hand being derived from SWIR's is sensitive to changes in the mangroves structural units (Kuenzer et al., 2011, Zhang et al., 2014) can portray the condition much competently.

Mangrove species assemblages have specific affinity and spatial preferences from the perspective of distance from water and elevation from mean sea level. These stands propagate spatially with diverse species composition and inconstant ecological parameters which induces uneven growth among same species individuals and vice versa. Different species having dissimilar health condition may appear similar entities when observed by remote sensing and therefore, gives rise to the confusion or fuzziness in their mapping. Here we present an approach for delineating species assemblage specific stress mapping based on DNVI developed from SWIR bands using fuzzy classification method. The objectives of the research were to (i) map the spatial distribution of mangroves based on their stress or health conditions and (ii) to delineate the mangrove species assemblage specific stress condition using fuzzy classification employing ground observation, DNVI and NDVI.

2. Methods

2.1 Study area

Sundarban is the largest deltaic contiguous mangrove patch in the world. The Indian part of the forest is subdivided into a core zone of 1700 km^2, manipulation zone of 2400 km^2, restoration zone of 230 km^2, and a development zone of 5300 km^2 (Nandy and Kuswaha, 2011). As reported by IUCN, it is a habitat to a wide range of flora; 334 plant species belonging to 245 genera and 75 families, 165 algae and 13 orchid species. The meso-macrotidal estuary gets inundated and exposed twice a day by diurnal tides having amplitude of 2.5–7 m. The soil texture is chiefly clayey-loam whereas certain parts also have sandy-loam and silty soils. The present study was conducted in a wildlife sanctuary (Figure 1) in the Indian part of Sundarban and although situated very close to human settlements, it is having almost no influence from anthropogenic activities.

2.2 Satellite image processing

Sentinel-2 cloud free image archived by European Space Agency was used for the study and downloaded from the Sentinel data hub (https://scihub.copernicus.eu/). The reflectance image is comprised of 13 bands having different spatial resolutions (Table 1). All the bands were resampled using ESA-Sentinel Application Platform (SNAP) freeware. We used 10 m and 20 m resolution bands for the classification purpose and the 60 m bands were used to derive the DNVI.

Table 1: Spatial and spectral resolution of Sentinel S2A MSI

Bands	Spatial resolution (m)	Central wavelength (nm)	Bandwidth (nm)
B1	60	443.9	27
B2	10	496.6	98
B3	10	560.0	45
B4	10	664.5	38
B5	20	703.9	19
B6	20	740.2	18
B7	20	782.5	28
B8	10	835.1	145
B8a	20	864.8	33
B9	60	945.0	26
B10	60	1373.5	75
B11	20	1613.7	143
B12	20	2202.4	242

It has been already depicted by Zheng et al. (2017) that for Sentinel 2 data, downscaling pixel size of a coarse resolution band performs better than upscaling with respect to classification accuracy or delineation capacity. Additionally, the upscaling could deprive the entire dataset from spatial information contained in the fine spatial resolution bands. DNVI developed from 60 m bands (resampled to 10 m for compatibility with NDVI) is used only as a thematic parameter for guiding the fuzzy convolution. The raster data was processed, analysed and interpreted with the help of ENVI software.

2.3 *In-situ* sampling

Field inventory for the health condition of different species and their assemblages were conducted during March 2016. Eighty ground locations with details of species, physiological conditions like health, slenderness coefficients (Vovides et al., 2014) of trees and substratum conditions were recorded using GPS 72 (Garmin Ltd.). The soil salinity, slenderness coefficient (ratio of total height to girth), canopy density- leaf area index were recorded for the assessment of the health of mangroves. Leaf architecture and condition (thickened and or short leaves, crumbled or flat lamina), tree structure (straight trunked or gnarled) and distance of trees from the intertidal zone which mutually indicate the health condition of mangroves were also recorded. Apart from that, as the weaker trees are more susceptible to insect infestations, the locations of such canopies were also recorded for the purpose. Random sampling was done in order to ensure the complete coverage of the study area and its floral compositions. In addition, the pure and mixed species assemblages were located precisely for their mapping.

2.4 Species mapping

Based on the field inventory and using Support vector machine (SVM) algorithm in ENVI (Exelisvis Inc., USA), the Sundarban mangrove area under consideration was delineated into different mangrove species, assemblage types and non-mangrove landcover including mudflats. Tree class abbreviations are elucidated in table 2. SVM is a non-parametric supervised learning model that exercise user defined signatures and has been used for precise mangrove mapping recently (Heumann 2011; Manna and Raychaudhuri, 2018).

Table 2: Abbreviations used for mapping classes

	Abbreviation	Species details
1	AA_m	*Avicennia alba* matured assemblages
2	AA_y	*Avicennia alba* young assemblages
3	AM	*Avicennia marina*
4	AM_sc	*Avicennia marina* scrub assemblages
5	AO	*Avicennia officinalis*
6	AR	*Agialites rotundifolia*
7	EA	*Excoecaria agallocha*
8	Mixed	Mixed tall assemblages
9	Mixed_sc	Mixed scrub assemblages
10	PP	*Phoenix paludosa*

2.5 Fuzzy classification

Sundarban mangroves having heterogeneous species composition provide an opportunity to map this fuzzy variation with respect to individual species using fuzzy classification technique where there is no precise threshold between two similar yet different targets. Such classification is a type of *soft classification* with certain degree of uncertainty of the classified image. The targets are classified with multiple membership values considering the probability of them belonging to any class, which is the actual scenario of a diversely populated forest. The ambiguity is put in order by fuzzy clustering where the information from neighbouring pixels helps determining the actual parent category.

The classification is based on fuzzy logic comprising the following steps. The reflectance image containing thirteen bands, each of 10 m spatial resolution was used to collect the signatures specific to a species or assemblage. The signature collection was executed by selecting thirty areas of interest (AOI) of different features and of different pixel counts based on ground survey, DNVI and species map. Based on the collected signatures, fuzzy classification was carried out considering two best classes per pixel. Using this classified image as the input along with the distance file of the two bands of DNVI and NDVI, fuzzy convolution was executed, which created a single classification layer of the total weighted inverse distance of all the classes in a window of pixels thereby creating a context based classification. The general expression for the total weighted distance of window for class *k* is given by

$$T(k) = \sum_{i=0}^{s} \sum_{j=0}^{s} \sum_{l=0}^{s} \frac{w_{ij}}{D_{ijl}(k)}$$

where *i* and *j* are row and column index of window respectively, of the window of size *s* (3×3 used here) and class value *k*, w_{ij} being the weight table for the window. *D(k)* represents the distance file value for each window element for class *k*. The block diagram shown in figure 2 represents the methodology in a schematic flowchart.

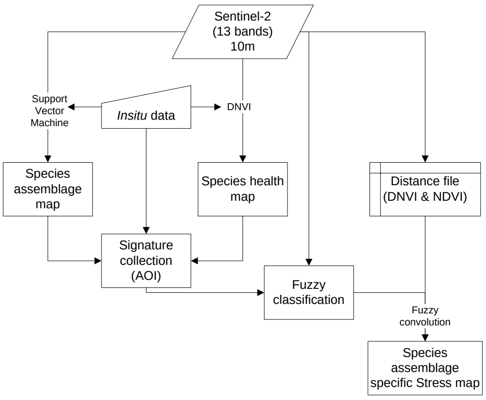

Figure 2: Schematic representation of the methodology used for species assemblage specific stress of mangroves

3. Results and discussion

The fuzzy convolution technique assigns the centre pixel of the running window within the class of the largest total inverse distance summed over the entire fuzzy classified bands. Classes with small distance values remain unchanged whereas those with large values may change to a neighbouring value, if sufficient number of neighbouring pixels with class value exists. In the present case (Figure 3a), 3×3 window size was used (Figure 3b). A larger window size (7×7) might lead to over-generalization (Figure 3c).

The health condition of mangroves is an apparently variable parameter, as their stand comprises different, congeneric species. Conventionally, the most popular vegetation index NDVI is used as indicator to several biophysical parameters including fractional vegetation cover estimates, leaf area index, vigour and even biomass (Curran et al., 1992, Jiang et al., 2006, Manna et al., 2014). However, several studies have depicted the saturating tendency of NDVI in predicting the biophysical properties of trees, especially of canopies which are mostly a voluminous and multi-strata entity. In mapping the overall health of a mangrove forest using remote sensing, an index like DNVI (Manna and Raychaudhuri, 2018) is capable of spatially portraying the stressed and healthy assemblages of mangroves. A comparative analysis (Figure 4) of NDVI with health index DNVI has depicted a linear relation with a saturating tendency at higher NDVI values.

It is concluded from the saturating tendency of NDVI (Figure 4) that the discrimination of mangroves health condition by DNVI is more efficient than that using NDVI as a proxy. The selective difference in their capabilities might be due to the spectral ranges of reflectance used to derive the indices. NDVI is derived using *red* and *near infrared* bands indicative of leaf pigments and cell structure, whereas DNVI is developed using *shortwave infrared* bands responsive to structural properties associated with stress conditions, such as water content, leaf biochemicals, protein, lignin and cellulose (Kuenzer et al., 2011, Zhang et al., 2014). A general stress map generated using DNVI indicates the distribution of saline blanks and stressed vegetation precisely (Figure 5a). The different regions in figure 5a are indicated by similar colours but all the mangroves under the same category do not belong to same species (Figure 5a, b).

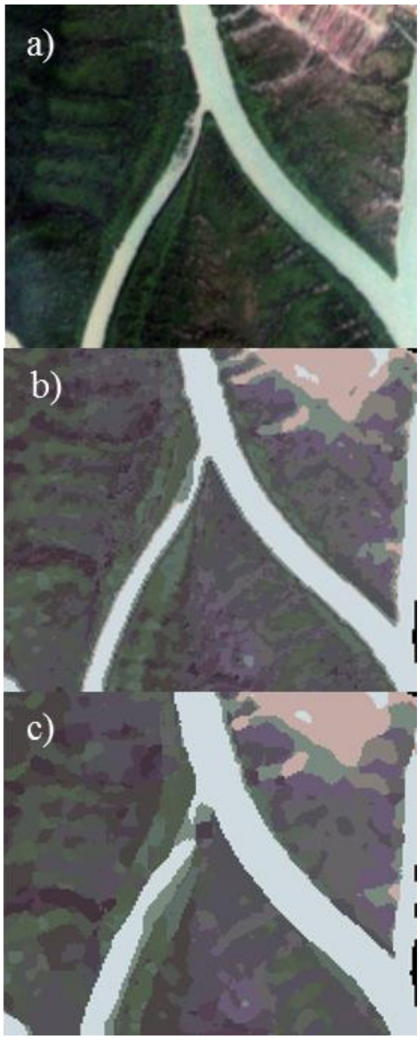

Figure 3: A part of the study area depicting a) the true colour composite from Sentinel-2 data, b) fuzzy convolution result using 3×3 window and, c) fuzzy convolution result using 7×7 window

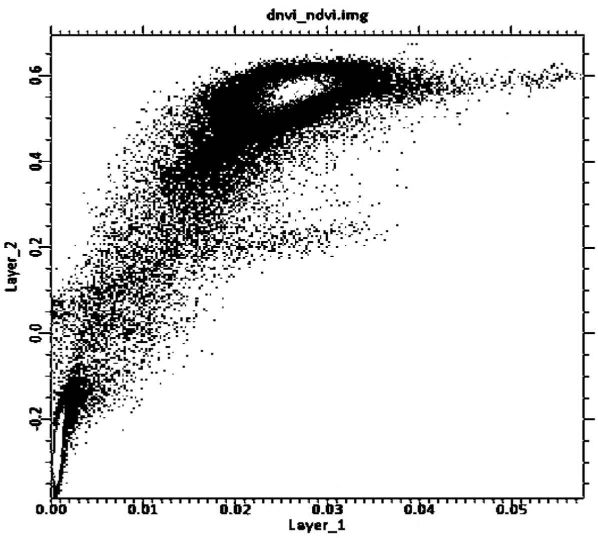

Figure 4: Scatter plot of DNVI (x axis) versus NDVI (y axis) depicting the saturating tendency of NDVI

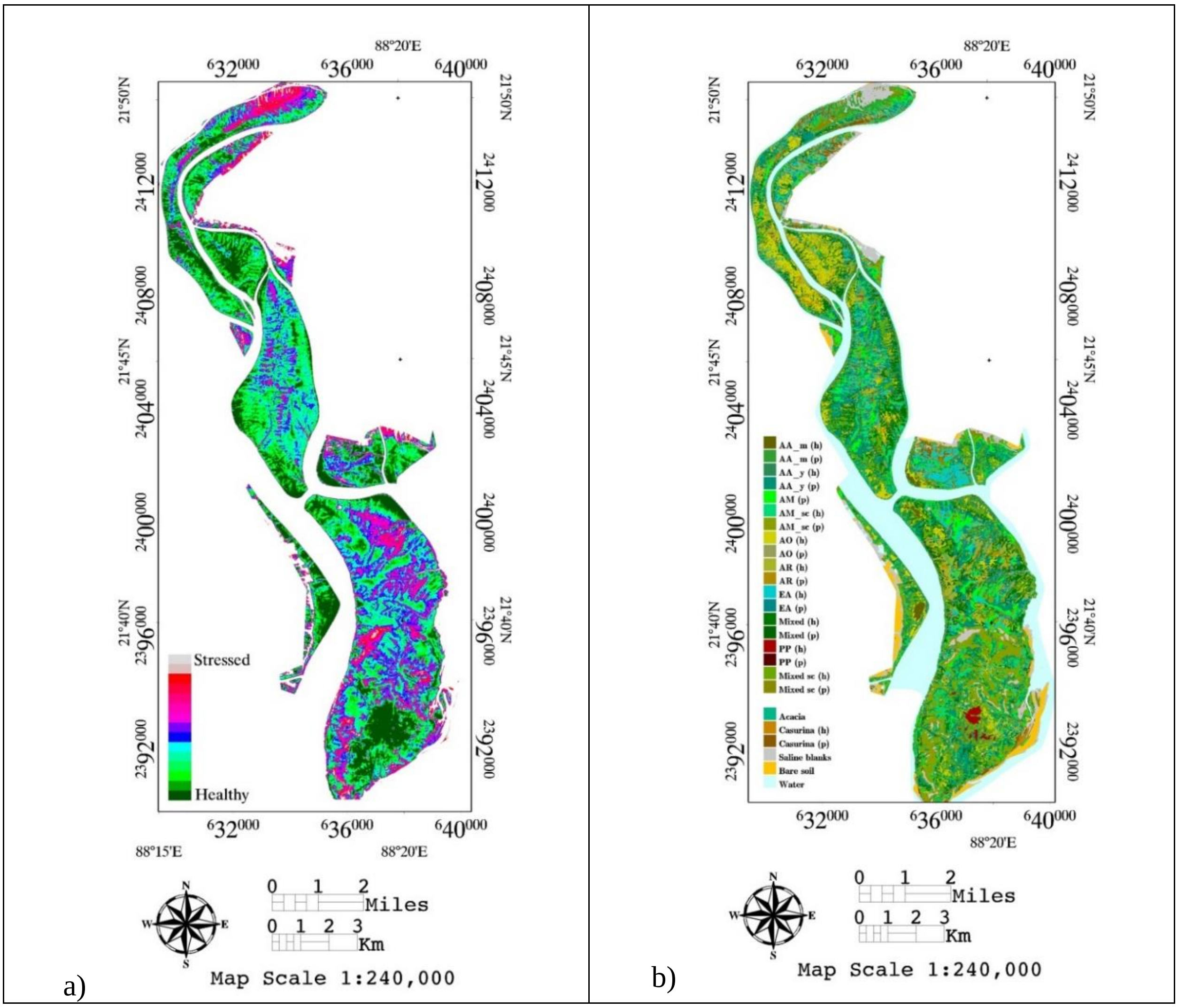

Figure 5: Maps of Lothian wildlife sanctuary, Sundarban showing a) DNVI based generalised stress map and b) Species assemblage specific stress map* derived using fuzzy classification. (* the legend details are provided in Table 2; h and p in parentheses indicate health and poor conditions respectively).

A similar index value for two different species does not indicate similar physiological conditions for both the candidates. Such variation in health condition might be due to their respective physiology, growing capability in particular eco-region and differential association with other species. The geographical variation also plays a crucial role in the growth and health conditions of mangroves. For instance, a species namely *Ceriops decandra* is reported to robustly grow up to a height of ≈ 5m in the Bangladesh part of Sundarban (Hossain et al. 2012), whereas this species is found to grow mostly as shrub, bushy and stunted in the Indian counterpart. A possible reason is the increasing salinity stress in Indian dominion due to gradual obstructions in paleo-channels bringing fresh water supply to the delta (Gopal and Chauhan, 2006). Moreover, in order to conserve and manage a forest stand with several species, the micro-level stress assessment is much more essential than representing a synoptic health status.

4. Conclusion

DNVI, a health index developed from Sentinel-2 high resolution free data and validated with airborne hyperspectral satellite data was utilized for mapping the stress of mangroves in Sundarban. The representative species assemblage specific stress map was generated using the fuzzy principle where the ground data, established species map, and DNVI and NDVI were used as parameters for training the parametric classifier. While NDVI has always been used as an indicator to various biophysical parameters of vegetation, this study revealed that in mapping the health it saturates disabling the fine distinction among assemblages of good health.

The implication of fuzzy classification and use of DNVI and NDVI for fuzzy convolution revealed the fuzzy nature of mangroves in its spatial distribution. The vertically multi-stratum canopied forest was mapped better using fuzzy classification than the fixed algorithm based hard classification methods. Given the observations and findings from the study, the approach highlighted the need of mapping the stress of different assemblages discretely that could not be portrayed by single stress image. The necessity of this approach is also supported by the fact that same index value for different mangroves does not indicate an equal health or stress. Furthermore, precise mapping of mangroves stress could be realized by plausible fusion of high resolution non-commercial data like Sentinel-2 with compatible microwave data for more realistic assessment of mangrove forests having complex morphology and community structure. Precise micro-mapping in the cases like the above requires a superior classification technique rather than a hard classification method, especially in the case of variable forest cover where the confusion probability is higher in multispecies natural system like Sundarban. Therefore, the stress mapping at species and assemblage level was done using fuzzy classification that resulted in fine scale health-stress map of the mangroves in study area.

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