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Review Article

Analysis of Remote Sensing based Vegetation Indices (VIs) for Unmanned Aerial System (UAS): A Review

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Abstract

Unmanned Aerial System (UAS) is an efficient tool to bridge the gap between high expensive satellite remote sensing, manned aerial surveys, and labors time consuming conventional fieldwork techniques of data collection. UAS can provide spatial data at very fine (up to a few mm) and desirable temporal resolution. Several studies have used vegetation indices (VIs) calculated from UAS based on optical- and MSS-datasets to model the biophysical parameters of the Earth surface. They have used different techniques of estimations, predictions and classifications. However, these results vary according to used datasets and techniques and appear very site-specific. These existing approaches aren't optimal and applicable for all cases and need to be tested according to sensor category and different geophysical environmental conditions for global applications. UAS remote sensing is a challenging and interesting area of research for sustainable land management.

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1 INTRODUCTION

Unmanned Aerial Systems (UAS) have been widely used in many applications such as vegetation monitoring (Merza and Chapman, 2011); agriculture (Walsh *et al.*, 2018; Marino and Alvino, 2019), hydro-geomorphological assessments (Casado *et al.*, 2016), hydrology, water conservation, water quality analysis (Koparan *et al.*, 2019), river characterization (Casado *et al.*, 2016; Larrinaga and Brotons, 2019), soil management (Oliveira *et al.*, 2019), urban mapping (Noor *et al.*, 2018), disaster management (Yang *et al.*, 2016; Carvajal-Ramírez *et al.*, 2019) including post-fire vegetation analysis (Fernández-Guisuraga *et al.*, 2018). At present, satellite based remote sensing has limitations such as resolutions, availability including frequency and flexibility, complicated image processing, higher costs etc. (Zhang and Kovacs, 2012; Wan *et al.*, 2018) whereas ground-based sensor systems have issues related to mobility (moving one place to another), cost-effectiveness and real time mapping (Zhang and Kovacs, 2012; Sankaran *et al.*, 2015; Caturegli *et al.*, 2019). However, UAS based techniques are useful for survey of relatively smaller area, but for efficient work it needs to be larger than 5 hectors (Wahab *et al.*, 2018). UAS is more efficient tool to bridge the gap between- 1) high expensive satellite and manned areal remote sensing and 2) labors and time-consuming conventional fieldwork techniques of data collection for environmental planning, management and monitoring (Wahab *et al.*, 2018).

The market revenue of UAS based remote sensing and mapping is booming since last decade (Colomina and Molina, 2014; Barbedo, 2019). At the same time scientific community and industry have remarkably involved with publications and production of essential equipment (Colomina and Molina, 2014). Many conferences/meetings were organized in this period and

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volumes were published by reputed organizations and publishers (Colomina and Molina, 2014). Many commercial, non-profit organizations and governmental agencies are involved and have invested their energies for research, development and applications of the UAS techniques.

Popular terms observed for this technique are Remotely-Piloted Aerial Systems (RPAS), 'Unmanned Aerial Vehicle' (UAV), 'aerial robot', 'drone' (Colomina and Molina, 2014), etc. International Civil Aviation Organization (ICAO) has coined the term RPAS and integrated this technology into 'international civil aviation system' (ICAO, 2011). UAS includes: 1) unmanned aircraft (UA), 2) a Ground Control Station (GCS) and 3) a communication data links (Colomina and Molina, 2014). 1) Aircraft trajectory: waypoints, strips, speed, attitude, etc. and 2) mission management: sensor configuration, triggering events, flying directions, etc. are important aspects during the mission. Micro- and mini- UAS vehicles are very sensitive to winds therefore 80% forward and 60-80% cross overlap are suggested to compensate errors occurred due to aircraft instability (Colomina and Molina, 2014). Four types of UAS are parachutes, blimps, rotocopters, and fixed wing systems (Sankaran *et al*., 2015). Further, stable imaging platforms have been suggested as solution to the problem of wind induced instability in UAV (Yang *et al*., 2016).

Colomina and Molina (2014) have explained different aspects of UAS: recent unmanned aircraft, navigation, sensing techniques, data processing techniques and photogrammetry. Novelties of the technique are very high resolution (centimeter level), low-cost equipment, powerful, sophisticated computer vision, robotics and geomatic engineering (Colomina and Molina, 2014; Gracia-Romero *et al*., 2019; Caturegli *et al*., 2019). Therefore, the advances of the technique are: 1) cost-effective: low weight, slow flight, speed and extended range, (Casado *et al*., 2016), 2), less fuel (Casado *et al*., 2016), 3), timely and on-demand data (Casado *et al*., 2016) and 4) safety mission (Casado *et al.* 2016). UAS can capture images even in cloudy conditions (Casado *et al*., 2016). This technique is more useful for large-scale low-altitude imaging and geospatial information (Colomina and Molina, 2014) for policy makers, regulatory bodies and mapping authorities.

UAS applications are detection and quantification of stress plants, prediction of yield, estimations of biomass and canopy cover, classifications of vegetation, assessment of plant heights, etc. (Barbedo, 2019; Oliveira *et al*., 2019; Durfee *et al*., 2019). Vegetation indices (VIs) show significant relationship with disparities in ground cover (Schut *et al*., 2018) including vegetation, soil characteristics (Oliveira *et al*., 2019), barren and impervious surfaces, water bodies etc. VIs are widely used for analysis of 1) precision agriculture: analysis of crop performance (Buchaillot *et al*., 2016; Marino and Alvino, 2019; Gracia-Romero *et al*., 2019), diseased crops/plants (Sandino *et al*., 2018; Javan *et al*., 2019), plant nutrients (Walsh *et al*., 2018), plant phenology (Park *et al*., 2019), plant height (Fathipoor *et al*., 2019), 2) preparation of DEM (Themistocleous, 2019), 3) management of covered soils (Oliveira *et al*., 2019), etc. Durfee *et al.* (2019) have used VIs for assessing the green cover at watershed level. Carvajal-Ramírez *et al.* (2019) have calculated fire severity indices for pre- and post-fire situations using MSS imageries captured by UAS.

Table 1. Types of Unmanned Aerial System

UAS types	Advantages	Limitations
Parachutes	Fly in calm condition (no wind).	Can operate in windy condition. Low speed and short flight time.
Blimps	Useful for area imaging. Capture clear optical images. Longer coverage of capture.	Unable to fly in windy condition.
Rotocopters	Widely used type for UAS. Fly at different altitudes (four to eight propellers). GPS-based navigation. Fly horizontally and vertically. Take-off and landing over very little space. Thermal, multispectral to hyperspectral sensor.	Low speed and short flight time.
Fixed wing systems	More speed and longer flight time. Waypoint navigation Multiple sensors	Limited hovering capabilities. Image blurring due to higher travel speed than the sensor.

Modified after Sankaran *et al*., 2015.

Walsh *et al.* (2018) have calculated VIs for Spring wheat thorough growing stages using UAS images and found positive significant relationship between calculated VIs values and measured plant nutrients. Javan *et al.* (2019) have successfully used UAV based VIs for detection and mapping of diseased Citrus plants. Buchaillot *et al.* (2016) have analyzed Maize performance in low nitrogen condition using VIs calculated based on UAS-MSS data in Zimbabwe. Marino and Alvino (2019) have analyzed the abilities of high resolution UAU images to detect the spatiotemporal variability of wheat crop in Italy. Caturegli *et al.* (2019) have analyzed the applicability of NDVI [Normalized Difference Vegetation Index] and DGCI [Dark Green Color Index] for detection of N content in plant life for precision agricultural management using UAS. Eng *et al.* (2018) and Cermakova *et al.* (2019) have used the VARI (Visible Atmospherically Resistant Index) for vegetation analysis. Park *et al.* (2019) have using UAV based color indices to quantify the leaf phenology of trees and species in tropical forest. Marcial-Pablo *et al.* (2018) have used VIs for estimations of vegetation fractions using UAV-RGB images. Therefore, UAS based VIs are very useful for analysis of plant nutrients, variability in crop performance, vegetation analysis, etc.

Researchers have used different methods and techniques for analysis of ground surface using VIs calculated from UAS based data. Yeom *et al.* (2019) have compered the plant growth pattern for conventional tillage (CT) and no-tillage (NT) agricultural lands using UAS based VIs. Wahab *et al.* (2018) have UAV based GNDVI to assess the growing stage wise vigor and yields of maize crops in Sub-Saharan Africa. Jiang *et al* (2019) have used UAV based VIs for estimation of above ground biomass (AGB) with TIN [Triangulated Irregular Network] based structure and metrological data. Fathipoor *et al.* (2019) have combined VIs with plant height estimated using UAV based DEM for crop yield prediction. Further, Niu *et al.* (2019) have compared VIs indices and point cloud-based plant height estimated using UAV-RGB images for estimation of AGB of maize crops. Oliveira *et al.* (2019) have successfully used and suggested Random Forest (RF) calculated from UAV based RGB and hyperspectral data for estimation and mapping of biomass production from grasses. Themistocleous (2019) has prepared DEM using five VI. Thus, VIs calculated using UAV based RGB and NIR data are used for planning and monitoring the environmental issues.

Recently, some researchers have reviewed the reported research on UAV technology (Xue and Su, 2017; Kadian and Khadanga, 2019; Asmaa *et al.*, 2019 Guo *et al.*, 2020), and its applications in agriculture (Zhang and Kovacs, 2012; Barbedo, 2019), urban planning (Noor *et al.*, 2018), communication (Indu and Singh, 2020), target tracking (Chen and Zhou), damage mapping (Kerle *et al.* 2020), related regulations and politics (Srivastava *et al.*, 2019). Further, Sankaran *et al.* (2015) have analyzed research reports on application of UAS-VIs for crop phenotyping. Xue and Su (2017) have analyzed the applications of more than 100 VIs for precision analysis of vegetation and environment. Barbedo (2019) have reviewed applications of UAV and imaging sensors for monitoring and assessing the plant stresses. Thus, it shows limited efforts for analysis of research published on applications of VIs from UAS based datasets. Therefore, the present study focuses on review of applications of VIs-UAS datasets for remote sensing analysis. The analysis discussed in the paper can be useful for preparation and application of UAS based datasets for analysis of biophysical parameters of the Earth surface for sustainable land management.

This article reviews the different aspects of UAS based datasets including sensors, spatial resolutions and techniques of data processing. Introductory section reviews the background of the paper with aims and objectives of the study and its applications. Section ‘data’ covers the types of sensor installed on the UAS platforms and spatial resolution of the data. Third section explains the techniques of data processing including radiometric- and geometric corrections, geo-referencing, image enhancement and classification techniques used in the research that are reported in different papers and articles. Last section discusses the finding and applications of the technology with reported limitations. The citations are listed at the end of the paper and complied information is tabulated.

2 DATA

2.1 Sensors

UAV-based remote sensing was beginning with small range of spectral bands: Red, Green and Blue (RGB). RGB images are powerful, low-coast and more practical source of data for performance analysis and monitoring crop cycles (Gracia-Romero *et al.*, 2019; Beniaich *et al.*, 2019). Recently, these systems are updated with multispectral (MSS) sensors with Red Edge (RE) and NIR bands (Yeom *et al.*, 2019) (Table 2). Therefore, VIs developed for traditional RS can be calculated using this data for various applications for agriculture management, water resources management, urban planning, forest management, etc. NIR found superior than RGB for precise vegetation analysis using different VIs (Yeom *et al.*, 2019). Research have reported results of UAV based crop performance analysis similar to data captured using ground-based sensors (Gracia-Romero *et al.*, 2019). Marcial-Pablo *et al.* (2018) have reported suitability of RGB based VIs for early season crop monitoring whereas MSS data for later season analysis of the crops. Further, Sandino *et al.* (2018) have used UAV-based hyperspectral images for mapping of Pathogens affected forest trees. Thus, UASs based RGB, MSS and hyperspectral datasets are available for analysis of biophysical parameters of the Earth surface using VIs for sustainable land management.

Table 2. Unmanned Aerial System Sensors

Sensor	Bands	Spatial resolution (cm) with flying height (m)	Authors	Calibration
RGB	R, G, B	0.51 (20) to 0.84 (30) 0.94(50) 5 (97)	Yeom *et al.* (2019) Niu *et al.* (2019) Gracia-Romero *et al.*, (2019) Marino and Alvino (2019)	Reflectance panel Camera dedicated to incident light sensor
NIR	RE and NIR	1.58 to 1.69 (40)	Yeom *et al.* (2019)	Ambient illumination sensor
	G, R and NIR	10(286)		
RGB and NIR	R, G, B and NIR	3(100)	Wahab *et al.* (2018); Marino and Alvino (2019)	Teflon calibration panel.
MSS	R, G, B, NIR, RE Six bands	1.2 (12) (50 suggested)	Javan *et al.* (2019) Guo *et al.* (2019)	Mini MCA 6 sensor
	12 bands: RGB, RE and NIR	2.6 (120)	Jiang *et al.* (2019)	Empirical linear model.
NDVI and RGB		5 (90)	Caturegli *et al.* (2019)	UAV based NDVI compared with ground based NDVI.
Hyperspectral	274 bands		Sandino *et al.* (2018)	
RGB, MSS and Hyperspectral	RGB MSS: B,G,RE and NIR Hyperspectral: 274	3.26 (60)	Vanegas *et al.* (2018)	Mica sense reflectance board
RGB MSS	RGB R, G, B, NIR, RE	2.02-3.0(40-50)	Durfee *et al.* (2019)	Resolutions vary according to the imagery and flying scheme.

2.2 Flying Time and Height

The flying time affects the sun light and angle, weather, atmospheric transference, plant phenology, etc. therefore, someone can select flying time considering these points. Lower sun angle gives higher contrast between red and green bands (Larrinaga and Brotons, 2019). However, Larrinaga and Brotons (2019) didn't find remarkable difference in performance of greenness indices calculated using data captured at different altitude. However, cell statistics and selection of optimal greenness index are depending on flying height of UAV. Image resolution varies according to the flying height (refer section 2.3: resolution) (Table 2). Therefore, researchers and UAS managers should carefully record the flying time and height arranged for RS data capturing. However, Larrinaga and Brotons (2019) have reported no-effect of flying heights (50 and 120m) on modeling for estimations for post-fire regenerations of Mediterranean forests.

2.3 Spatial Resolution

Traditionally, course resolution images captured using standard remote sensing camera installed on manned aircrafts have been used to meet requirements of small object detections (Casado *et al.*, 2016). UAS provides data at fine resolution (finer than 1cm) with desired temporal resolution (Sankaran *et al.*, 2015). This technology is very promising for management of precision agriculture due to fine resolution. Finer spatial and desired temporal resolution allows detecting the plant growth patterns (Yeom *et al.*, 2019), disease effects (Javan *et al.*, 2019), etc. Yeom *et al.* (2019) have used data UAV based MSS images at resolution of 0.51 to 0.84 cm (RGB) and 1.58 to 1.69 cm (NIR) for analysis of tillage effects in agriculture using VIs. Javan *et al.* (2019) have used UAV MSS image at 2 cm resolution for detection of greening disseized Citrus trees in Iran. Niu *et al.* (2019) acquired the data at 0.8 cm resolution for estimation of AGB of Maize crop. Caturegli *et al.*, (2019) used UAV based images at 5 cm for detection of N content in plant leaf using NDVI and DGCI. Further, Casado *et al.* (2016) have used three UAV resolutions: 2.5, 5 and 10cm for automated Hydro-morphological characterization of 1.4 km river reach. Resolution vary according to flying height and suggested effective flying height is 50 m to capture the UAV based images (Guo *et al.*, 2019). Oliveira *et al.* (2019) have achieved 0.7 cm and 5 cm ground resolution for photogrammetric and hyperspectral imageries captured at 50 flying height. Buchaillot *et al.* (2019) have used UAV RGB images of 0.03 cm/pixel captured at same flying height (50m) for calculation of VIs. Durfee *et al.* (2019) have achieved higher spatial resolution for RGB images than the MSS. Thus, images captured using UASs can give very finer resolution (less than 1 cm e.g. 0.5 cm) which varies according to the flying height of the UAV.

3 TECHNIQUES USED FOR REMOTE SENSING OF LAND

3.1 Radiometric Corrections

Simply ground reflectance panel, ambient illumination sensors and mean DN values calculated using white reference were used for calibration of UAV based sensing images (Yeom *et al.*, 2019; Javan *et al.*, 2019). Yeom *et al*. (2019) have calibrated images using ground reflectance panel and ambient illumination sensors for frame to frame to characterization for precise comparisons throughout day and growing season. Javan *et al.* (2019) have used reflectance panel and mean DN values calculated for values of images collected before and after flight for all 5 bands (Javan *et al.*, 2019). Guo *et al.* (2019) have used three pseudo targets and four boards radiometric calibration using handheld device specially designed for spectral measurements. However, calibration of images captured using UAV platforms is quite difficult due to small FOC and different imaging conditions for each image (Guo *et al.*, 2019). Most of time researchers are using UAV based images without calibration or with coarse calibrations (Guo *et al.*, 2019). Therefore, Guo *et al.* (2019) have used linear regression model for calibration of UAV based MSS images captured at different height for vegetation analysis using VIs. They have reported that atmospheric distortions appear more in images with increasing platform height and suggested universal calibration equation and LRM for images acquired sunny, little cloudy and cloudy weather. RGB images preferred for cost-effective operations without calibration systems. Therefore, they need to be calibrated using reflectance panels (Yeom *et al.*, 2019). Linear calibration model was found useful to calibrate the image digital numbers with corresponding ground reflectance values (Yeom *et al*., 2019).

Normalized RGB bands (equations (1, 2 and 3)) were used before calculation of VIs in many research projects (Beniaich *et al*., 2019; Li *et al*., 2019; Yeom *et al*., 2019, etc.). However, many studies have used RGB data without this normalization for different applications like crop yield (Wahab *et al.*, 2018). Further, Larrinaga and Brotons (2019) have used normalized ‘G’ as GCC [green chromatic coordinate] for calculation and successfully used for estimations of post fire regeneration of forests with higher accuracy than ExGI.

Researchers have used band conversions for specific studies using UAV data. Technique suggested by Karcher and Richardson (2013) was used for conversion of RGB pixel values into HSB [Hue, Saturation and Brightness] values for analysis of leaf nitrogen status (Caturegli *et al.*, 2019). DN values were transformed to surface reflectance using empirical linear model using six nominal reflectance values to calculate the canopy surface of Rice crop (Jiang *et al*., 2019). Ribeiro-Gomes *et al*. (2017) have calibrated thermal cameras using a blackbody source Hyperion R Model 982 for UAV application of agriculture. Thus, some of them have used different models and techniques for radiometric calibration of UAV base RS datasets.

3.2 Geo-referencing

Image clarity and analytical preciseness are fully relied on geo-referencing of image captured using multi-lens sensors (Javan *et al.*, 2019). Distortions in color presentation increase with increasing number of pixels as error in registration. Ortho-mosaic image generation based geo-referencing of captured images has been used to achieve acceptable error (Javan *et al.*, 2019). Javan *et al.* (2019) have accepted error less than pixel size (0.6). Locational information (latitude, longitude and height) of Ground Control Points (GCP) was commonly used to achieve geometric accuracy of UAV based images (Vanegas *et al.*, 2018; Guo *et al.*, 2019). Wahab *et al.* (2018) have used 4 × 4 subplots for geo-referencing the images in GIS environment. Vanegas *et al.* (2018) have used Geoscience Australia online service selection of precise (3cm accuracy) GPS points instead of GPS information with course accuracy (5 to 10 m). Internal navigation systems with GPS are helpful to solve the problem of geo-referencing of RS images (Lulla *et al.*, 2004). Further, Masiero *et al.* (2017) have used low cost Ultra-Wide-Band (UWB) system for direct geo-referencing of UAV based images with average ground positioning error of about 0.18 m.

3.3 Spectral Indices

Vegetation indices calculated based on images captured using UAV have been widely used for vegetation analysis, monitoring water bodies, preparation of DEM, etc. Themistocleous (2019) has compared efficiency of six VIs (RGI, RGBVI, GLI, VARI, NGRDI and ERGBVE) for preparation of DEM and found Enhanced Red-Green-Blue Vegetation Index (ERGBVE) more useful. Themistocleous (2019) has claimed his invention to the ERGBVE. Vegetation indices have been used for monitoring small water bodies (Cermakova *et al.*, 2019). UAV based RGB VIs gives similar results for crop performance to ground based data (Gracia-Romero *et al.*, 2019).

VIs is widely used for agricultural applications including estimations of leaf area, canopy analysis, plant nutrients (nitrogen status), biomass estimations, crop yield, etc. Researchers have estimated good relationship of VIs with measured plant nutrients (Walsh *et al.*, 2018). Walsh *et al.* (2018) have successfully analyzed Nitrogen (N) concentration in leaves of Spring wheat in USA. They found ‘one to one’ relationship with estimated N concentration measured for NDVI and model-based relationship of CL_{green} with measured values of plant N. Further, Buchaillot *et al.* (2019) have evaluated performance of Maize Genotype under low N condition using NDVI and leaf Chlorophyll content calculated UAV-based image RGB data. Caturegli *et al.* (2019) have compared the efficiency of NDVI with DGCI for detection of life nitrogen content on Bermuda grass hybrid and tall fescue in Pisa. DGCI shows significant correlation with N content in plant life (Caturegli *et al.*, 2019). Javan *et al.* (2019) have used 16 VIs for detection of greening diseased Citrus plants in Iran using MSS data captured by UAV based remote sensors. Niu *et al.* (2019) have been successfully used VIs calculated using UAV-RGB VIs with optimized model for estimation of AGB. They have combined VIs values with modeled plant height for estimations of AGB.

VI indices can be useful to detect and calculate disease severity based on physiological status of tree leaves including biomass, leaf area, chlorophyll, water content, carotenoid content, anthocyanin content, etc. (Bendig *et al.*, 2015; Jansen *et al.*, 2014). Jansen *et al.*, (2014) have calculated NDVI, PRI [Photochemical Reflectance Index], SIPI [Structure Insensitive Pigment Index], PSSR [Pigment Specific Simple Ratio] WI [Water Index], CRI [Carotenoids Reflectance Index], ARI [Anthocyanin Reflectance Index], PSND [Pigment Specific Normalized Difference], NDWI [Normalized Difference Water Index], LWI [Leaf Water Index] and CLSI [*Cercospora* Leaf Spot Index] for analysis of physiological status of vegetation. Bendig *et al.* (2015) have invented MGRVI and the RGBVI for biomass estimations of crops. Larrinaga and Brotons (2019) have calculated ExGI [Excess Green Index], GCC [Green Chromatic Coordinate], VARI [Visible Atmospherically Resistant Index] and GRVI [Green Red Vegetation Index] for post fire analysis of the forest.

Table 3. Unmanned Aerial System based Vegetation Indices

Techniques	Descriptions	Authors
RGB normalization		
R	$R = \frac{R}{R+G+B}$ (1)	Li *et al.* (2019); Beniaich *et al.* (2019)
G	$G = \frac{G}{R+G+B}$ (2)	Li *et al.* (2019); Beniaich *et al.* (2019)
B	$B = \frac{B}{R+G+B}$ (3)	Li *et al.* (2019); Beniaich *et al.* (2019) Larrinaga and Brotons (2019)
Difference Vegetation Index	$DVI = NIR - Red$ (4)	Albetis *et al.* (2017)
Greenness Index	$GI = \frac{G}{R}$ (5)	Javan *et al.* (2019) Albetis *et al.* (2017)
Red-Green Ratio Index (RGRI)	$RGRI = \frac{R}{G}$ (6)	Wan *et al.* (2018)
Green Ratio Vegetation Index (Modified Anthocyanin Content Index)	$GRVI = \frac{NIR}{G}$ (7)	Javan *et al.* (2019) Albetis *et al.* (2017)
Anthocyanin Content Index	$ACI = \frac{G}{NIR}$ (8)	Albetis *et al.* (2017)
Simple Ratio Index	$SRI = \frac{NIR}{R}$ (9)	Wan *et al.* (2018) Javan *et al.* (2019)
Modified Red Edge Simple Ratio	$SR_m = \frac{NIR-B}{RE-B}$ (10)	Javan *et al.* (2019)
Normalized Difference Vegetation Index	$NDVI = \frac{NIR-R}{NIR+R}$ (11)	Javan *et al.* (2019); Yeom *et al.* (2019) Sandino *et al.* (2018) Albetis *et al.* (2017); Durfee *et al.* (2019)
Soil-Adjusted Vegetation Index	$SAVI = \frac{(NIR-R)\times(1+L)}{NIR+R+L}$ (12)	Albetis *et al.* (2017)
Optimized Soil-Adjusted Vegetation Index (OSAVI)	$OSAVI = \frac{NIR-R}{NIR+R+0.16}$ (13)	Marino and Alvino (2019)
Renormalized Difference Vegetation	$RNDVI = \frac{NIR-R}{\sqrt{NIR+R}}$ (14)	Javan *et al.* (2019)

Index		
Normalized Green Difference Vegetation Index	$NGDVI = \frac{NIR-G}{NIR+G}$ (15)	Wahab *et al.* (2018); Sandino *et al.* (2018) Javan *et al.* (2019); Yeom *et al.* (2019) Albetis *et al.* (2017)
Green-Red Vegetation Index (G-Rvi)	$G-RVI = \frac{G-R}{G+R}$ (16)	Javan *et al.* (2019) Themistocleous (2019); Yeom *et al.* (2019) Niu *et al.* (2019) Albetis *et al.* (2017)
Structure Insensitive Pigment Index	$SIPI = \frac{NIR-B}{NIR-R}$ (17)	Javan *et al.* (2019)
Modified Red Edge Normalized Difference Vegetation Index	$NDVI_m = \frac{NIR-RE}{NIR+RE-2B}$ (18)	Javan *et al.* (2019)
Red Edge Normalized Difference Vegetation Index	$\mathrm{RENDVI} = \frac{NIR-RE}{NIR-RE}$ (19)	Javan *et al.* (2019); Yeom *et al.* (2019)
Triangular Vegetation. Index	$TVI = 0.5[120(NIR-G)-200(R-G)]$ (20)	Javan *et al.* (2019)
Modified Triangular Vegetation Index-1	$MTVI_1 = 1.2[1.2(\mathrm{NIR}-\mathrm{G})-2.5(\mathrm{R}-\mathrm{G})]$ (21)	Javan *et al.* (2019)
Modified Triangular Vegetation Index-2	$MTVI_2 = \frac{1.5[1.2(\mathrm{NIR}-\mathrm{G})-2.5(\mathrm{R}-\mathrm{G})]}{\sqrt{(2NIR+1)^2-(6NIR-5\sqrt{R0})-0.5}}$ (22)	Javan *et al.* (2019)
Modified Chlorophyll Absorption In Reflectance Index	$MCARI_1 = 1.2[2.5(NIR-R)-1.3(NIR-G)]$ (23)	Javan *et al.* (2019)
Chlorophyll Index	$CI = \frac{NIR}{G}-1$ (24)	Javan *et al.* (2019); Yeom *et al.* (2019)
Red Edge Chlorophyll Index	$RECI = \frac{NIR}{RE}-1$ (25)	Yeom *et al.* (2019) Albetis *et al.* (2017)
Infrared Percentage Vegetation Index	$\mathrm{IPVI} = \frac{NIR}{NIR+R}$ (26)	Javan *et al.* (2019)
Normalized Excess Green Index	$RGBVI = (2G-R-B)/(2G+R+B)$ (27)	Yeom *et al.* (2019) Wan *et al.* (2018) Cermakova *et al.* (2019)
Normalized Green-Red Difference Index	$NGRDI = (G-R)/(G+R)$ (28)	Wan *et al.* (2018) Cermakova *et al.* (2019); Buchaillot *et al.* (2019); Li *et al.* (2019); Larrinaga and Brotons (2019)
Modified Green-Red Difference Index	$MGRDI = (G^2-G^2)/(G^2+G^2)$ (29)	Li *et al.* (2019) Yeom *et al.* (2019)
Woebbecke Index	$WI = (G-B)/(R+G)$ (30)	Li *et al.* (2019)
Kawashima Index	$KI = (R-B)/(R+B)$ (31)	Li *et al.* (2019)
Red-Green-Blue Vegetation Index	$RGBVI = ((G\times G)-(R\times B))/((G\times G)+(R\times B))$ (32)	Cermakova *et al.* (2019); Li *et al.* (2019)
Anthocyanin Reflectance Index	$ARI = Green^{-1}-RedEdge^{-1}$ (33)	Albetis *et al.* (2017)
Modified Anthocyanin Reflectance Index	$MARI = (Green^{-1}-RedEdge^{-1})\times NIR$ (34)	Albetis *et al.* (2017)
Normalized Difference Spectral Index (NDSI: 944, 758)	$(R_{\lambda 1}-R_{\lambda 2})/(R_{\lambda 1}+R_{\lambda 2})$ (35)	Wan *et al.* (2018)
Visible Atmospherically Resistant Index	$VARI = (G-R)/(G+R-B)$ (36)	Cermakova *et al.* (2019); Eng *et al.* (2018) Larrinaga and Brotons (2019)

Enhanced Red-Green-Blue Vegetation Index	$ERGBVE = \pi \times ((G^2 - (R \times B)) / (G^2 + (R \times B))$ (37)	Themistocleous (2019)
Excess RGB Indies		
Excess Green Vegetation Index	$ExGVI = 2G - R - B$ (38)	Cermakova *et al.* (2019); Li *et al.* (2019); Yeom *et al.* (2019)
Excess Red Vegetation Index	$ExRVI = 1.4R - G$ (39)	Li *et al.* (2019)
Excess Blue Vegetation Index	$ExRVI = 1.4B - G$ (40)	Li *et al.* (2019)
Excess Green Minus Excess Red	$ExGR = ExGVI - 1.4R - G$ (41)	Li *et al.* (2019); Yeom *et al.* (2019); Holman *et al.* (2019)
Vegetative	$G/(R^a B^{(1-a)}), \alpha = 0.667$ (42)	Wan *et al.* (2018) Li *et al.* (2019)
Texture Indices		
Normalized Difference Texture Indices	$NDTI(T_1, T_2) = (T_1 - T_2)/(T_1 + T_2)$ (43)	Li *et al.* (2019)
Soil Adjusted Vegetation Index	$SAVI = \frac{(NIR-R)(1+\alpha)}{NIR+R+\alpha}, \alpha = 0.5$ (44)	Sandino *et al.* (2018) Yeom *et al.* (2019)
Optimized Soil Adjusted Vegetation Index	$OSAVI = \frac{(NIR-R)(1+\alpha)}{NIR+R+\alpha}, \alpha = 0.16$ (45)	Yeom *et al.* (2019); Durfee *et al.* (2019)
Modified Soil Adjusted Vegetation Index	$MSAVI = \frac{2NIR+1-\sqrt{(2NIR+1)^2-8(NIR-R)}}{2}$ (46)	Yeom *et al.* (2019)
Dark Green Color Index	$DGCI = \left[\frac{(Hue)-60}{60} + (1-(Saturation))\right\| + (1-(Brightness))]/3$ (47)	Caturegli *et al.* (2019)
Phylloxera Indeces	$PI1 = (R_{522} - R_{504}/(R_{522} + R_{504})$ (48) $PI2 = (R_{551} - R_{562}/(R_{551} + R_{562})$ (49) $PI3 = (R_{700} - R_{680}/(R_{700} + R_{680})$ (50) $PI4 = (R_{782} - R_{700}/(R_{782} + R_{700})$ (51) $PI5 = (R_{782} - R_{671}/(R_{782} + R_{671})$ (52) $PI6 = (R_{680} - R_{563}/(R_{680} + R_{563})$ (53)	Vanegas *et al.* (2018)
Color Index of Vegetation	$CIVE = 0.441 \times R_R - 0.881 \times R_G + 0.385 \times R_B + 18.78745$ (54)	Wan *et al.* (2018) Niu *et al.* (2019)
Total Ratio Vegetation Index	$TRVI = 4[(NIR - R)/(NIR + R + G + B)]$ (55)	Durfee *et al.* (2019)
Triangular Greenness Index	$TGI = -0.5[(\lambda R - \lambda B)/(R - G) - (\lambda R - \lambda G)(R - B)]$ (56)	Durfee *et al.* (2019)
Vegetation Index	$VEG = \frac{R_G}{R_{R}\alpha \times R_{B}(1-\alpha)}, \alpha = 0.667$ (57)	Niu *et al.* (2019)

Researchers have used VIs for analysis of vegetation fractions, plant growth, crop height and yield, crop diseases, etc. Marcial-Pablo *et al.* (2018) have used three RGB based Excess Green (ExG), Color Index of Vegetation (CIVE), and Vegetation Index Green (VIg) and three NIR-based Normalized Difference Vegetation Index (NDVI), Green NDVI (GNDVI) and Normalized Green (NG) for estimation of vegetation fractions. Yeom *et al.* (2019) have analyzed 5 RGB and 8 NIR based VIs for plant growth comparison from conventional tillage (CT) and no-tillage (NT) fields. Crop yield has relationship with crop height which can be detected using UAV based images (Fathipoor *et al.*, 2019). Fathipoor *et al.* (2019) have estimated crop yield using VIs viz. visible atmospherically resistant index, NDVI and excess red in combination of estimated crop height estimated using UAV based DEM model. Sandino *et al.* (2018) have calculated NDVI, GNDVI, SAVI and MSAVI2 using UAV-based hyperspectral data for mapping of Pathogens affected forest trees. MSAVI and OSAVI are found more useful for plant growth analysis (Yeom *et al.*, 2019). Albetis *et al.* (2017) have used different vegetation indices for detection and comparison with biophysical parameters for analysis of Grapevine disease using images captured by UAV.

3.4 RGB-Vegetation Indices

UAV-RGB based vegetation indices have great potential of high precision and low cost assessment, planning and monitoring of agriculture, water resources, settlements, deserters, etc. Caturegli *et al.* (2019) have used RGB based vegetation indices for analysis and mapping of crop nitrogen at large area. Buchaillot *et al*. (2019) have reported better potential of UAV based RGB VIs for estimations of crop analysis.

Kauth and Thomas (1976) have transformed row Landsat data into greenness index. Larrinaga and Brotons (2019) have calculated the greenness indices (ExGI, GCC, GRVI and VARI) for analysis of post fire regeneration of Mediterranean forests. Wan *et al.* (2018) have used Red-Green Ratio Index (RGRI) for estimations of crop flower numbers (Table 3). RGRI index is useful 'to analysis the angular sensitivity of vegetation indices' (Wan *et al.*, 2018) and referred as an index of anthocyanin content in vegetation (Gamon and Surfus, 1999).

Several researchers have used Normalized Green-Red Difference Index (NGRDI) after Rouse *et al.* (1973) analysis of vegetation covers (Larrinaga and Brotons, 2019). Green vegetation reflects maximum amount of energy in the form of green and NIR spectral bands. They absorb radiations through blue and red spectral bands (Jiany *et al*, 2008). Therefore, this index is similar to NDVI calculated using band-G and -R of RGB image. Green reflects more than red from vegetation, red reflected more than green from soil and almost same reflectance occurred from water and ice. Therefore, NGRDI estimates positive, negative and near-zero for vegetation, soils and water-snow. This is promising indices for estimations of biomass (Bendig *et al*., 2015). Wan *et al.* (2018) have used this index for estimations of flowers of oilseeds. Further, Buchaillot *et al.* (2019) have used NG-RVI for estimation of N in maize crops in Nigeria. This index shows difference and signal structure than the NDVI.

NGRDI is similar to NDVI for calculations (Buchaillot *et al.*, 2019). Buchaillot *et al.* (2019) have calculated NGRDI (equation) using UVA based RGB data for estimations of crop yield:

$$NGRDI = \frac{R550-R670}{R550+R670} \quad (58)$$

Further, Buchaillot *et al*. (2019) have reported new RGB based VIs: NDLab and NDluv indices with performance similar to grain yield (GY) models.

$NGRDI = (G - R)/(G + R)$ (59) (Cermakova *et al.*, 2019)

Excess Green Red (ExGR) index (equation (4)) is useful for analysis of complex canopy structure (Wan *et al.*, 2018). Therefore, this index shows significant agreement with green vegetation and used to mask the area with green vegetation (Threshold >0) (Holman *et al.*, 2019). Larrinaga and Brotons (2019) have used successfully ExGR for analysis post fire regeneration of forest. It was used for estimations of crop flower numbers (Wan *et al.*, 2018).

$\text{ExGR} = 2 \times G - R - B$ (60) (Cermakova *et al.*, 2019)

ExGR shows potential to get precise vegetation differences (Yeom *et al*., 2019) and Beniaich *et al*. (2019) have reported better performance for soil cover analysis. Further, Cermakova *et al.* (2019) have used Normalized Excess Green Index (equation (61)):

$\text{NExGR} = (2 \times G - R - B)/(2G + R + B)$ (61) (Cermakova *et al.*, 2019)

This index is known as different names like Leaf Area Index (LAI), Green Leaf Index (GLI), Red Green Blue Vegetation Index (RGBVI), etc.

Bendig *et al.* (2015) have developed Red-Green-Blue Vegetation Index (RGBVI) (equation (62)) for estimation the plant height to estimate biomass of summer barley crop.

$RGBVI = ((G \times G) - (R \times B))/((G \times G) + (R \times B))$ (62) (Cermakova *et al.*, 2019)

They have reported potentials of RGBVI for vegetation analysis with need of further testing in different geophysical environmental situations. Modified GRVI (MGRVI) can be considered as an indicator of plant phenology and useful for estimations of biomass (Wan *et al.*, 2018). MGRVI shows potential of precise differences in vegetation characteristics (Yeom *et al.*, 2019). Therefore, Bendig *et al.* (2015) have modified GRVI (MGRVI) for estimation of the plant height to estimate biomass of summer barley crop. Wan *et al.* (2018) have used this index for estimating the number of flowers of oilseeds. Further, Excess Green Minus Excess Red (EXGR) proposed by Meyer and Neto (2008) have been suggested for separation from soil and backgrounds (Beniaich *et al*., 2019). They have used normalized values for RGB for estimations of EXGR. Themistocleous (2019) has calculated Enhanced Red-Green-Blue Vegetation Index (ERGBVE) and found more efficiency for estimation of DEM compared to other VI.

Dark Green Color Index **(**DGCI**)** values vary from 0 (very yellow) to 1(dark green). Caturegli *et al.* (2019) have calculated DGCI pixel values from RGB pixel values and compared with NDVI values to check the efficiency for detection of leaf nitrogen content. Further, Gitelson *et al.* (2002) have used Visible Atmospherically Resistant Index (VARI) for correction of indices for atmospheric effects. This index shows significant correlation with crop height estimated using UAV based DEM and crop yield in Iran (Fathipoor *et al.*, 2019). Wan *et al.* (2018) have used this index for estimations of flower numbers of oilseed rape. Larrinaga and Brotons (2019) have compared VARI (equation (63)) for analysis of post fire analysis of forest cover.

$VARI = (G - R)/(G + R - B)$ (63) (Cermakova *et al.*, 2019).

Excess Red shows positive correlation with crop height estimated using DEM prepared based on AUV images (Fathipoor *et al.*, 2019). Wan *et al.* (2018) have used color index for flower number estimations for oilseed crops. Niu *et al.* (2019) have used CIVE for estimation for AGB in China. Vegetativen (VEG) was also used for estimations for flowering classes of oilseed by Wan *et al.* (2018).

3.5 NIR-Vegetation Indices

3.5.1 *Simple Ratio Index*

SRI is mainly relating with crop physiology (Wan *et al.*, 2018). Wan *et al.* (2018) have used simple ratio index (equation (64)) for estimations of flower numbers of oilseeds after Jordan (1969). Leaves absorb red than the infrared therefore greater ratio represents comparatively more canopy cover (Jordan, 1969). Wan *et al.* (2018) found significant correlation with number of flowers of oilseeds.

$$SRI = \frac{R_{944}}{R_{758}} \qquad (64)$$

3.5.2 *Normalized Difference Vegetation Index (NDVI)*

Since NDVI was invented (1970), various VIs was developed using new spectral bands according to objectives of the study (Yeom *et al*., 2019). Rationing is the strength of NDVI which reduces multiplicative noise in multi-image data (Bhagat, 2012). Band-Red has ability to discriminate contrast between vegetation and non-vegetation whereas NIR is more sensitive to plant Chlorophyll. Therefore, NDVI is more superior than the RGB based indices. UAV based VIs show significant relationship with remote sensing based NDVI (Schut *et al.*, 2018). Therefore, UAV-based NDVI was used widely for vegetation analysis including forest classification, plant stress analysis (Caturegli *et al.*, 2019), crop nutrient detection (Walsh *et al.*, 2018; Buchaillot *et al.*, 2019; Caturegli *et al.*, 2019), crop/plant disease detection (Albetis *et al.* 2017; Javan *et al*., 2019), etc.

Caturegli *et al.* (2019) have successfully collected ground based direct NDVI output of captured reflectance at Red region (660 nm) and NIR region (780 nm) using Handheld Crop Sensor (HCS) for estimations of leaf nitrogen content. Holman *et al.* (2019) have reported the poor accuracy of NDVI calculated from the image captured using altered camera from R to NIR. Ratio between red and NIR remain unchanged when biomass increases (Jiang *et al*., 2019). Therefore, Jiang *et al.* (2019) have combined NDVI data with TIN based structural feature for precise estimation of AGB of rice crop. Fathipoor *et al.* (2019) have found significant correlation of NDVI with crop height and crop yield. Albetis *et al.* (2017) have compared NDVI with biophysical characteristics for detection of vineyard disease. Marino and Alvino (2019) have used this index for analysis of variability in vegetation cover. However, NDVI is not able to distinguish the typical disease (viz. phylloxera infestation) stress from stress cases by other sources and thermal imagery suggested to overcome this limitation (Vanegas *et al*., 2018).

3.5.3 *Green Normalized Difference Vegetation Index (GNDVI)*

Green Normalized Difference Vegetation Index is similar to NDVI uses visible band-green instead of band-red (Sankaran *et al.*, 2015). Band-INR and G have good abilities to estimate the density and intensity of vegetation cover using solar radiation (Wahab *et al.*, 2018). Reflectance in band-G is more sensitive to plant leaf Chlorophyll and plant health (Wahab *et al*., 2018). Burke and Lobell (2017) pointed that Band-G is more useful to capture the disparity in nutrient deficiency and therefore crop yield. Therefore, this index is more sensitive to wide range of Chlorophyll and efficient for vegetation analysis than the Normalized Difference Vegetation Index (NDVI) (Gitelson and Merzlyak, 1998). Wahab *et al.* (2018) have calculated the GNDVI for estimation of vigor and yield of Maize crop. It also shows stronger relation with drought stressed and non-stressed condition crops. Marcial-Pablo *et al.* (2018) reported superiority of GNDVI for vegetation fraction analysis.

Further, Marino and Alvino (2019) have used Soil-adjusted vegetation index (OSAVI) for estimation of variation in vegetation cover of wheat for yield analyses. Leaf Water Index (LWI) and Two-Dimensional Smoothing Kernels also used for this analysis.

3.5.4 *Combinations of Indices (COI)*

Some of the researchers have combined RGB indices for detection and estimations of AGB above ground biomass]. Niu *et al.* (2019) have combined (equation (65)) ExG, ExGR, CIVE and VEG for this purpose as:

$$COI = 0.25 \times ExG + 0.3 \times ExGR + 0.33 \times CIVE + 0.12 \times VEG \qquad (65)$$ after Niu *et al.* (2019)

Wan *et al.* (2018) have suggested combinations of various VIs (RGRI and NDSI (944, 758)) calculated using UAV-based RGB datasets for estimations for flowing numbers of oilseed ripe.

3.5.5 *Estimation, Prediction and Classification Techniques*

Researchers have used Support Vector Machine (SVM), Point Cloud (PC), Simple Linear Regression (SLR), Simple Exponential Regression, Random Forest (RF), Partial Least Squares Regression (PLSR) Model, Digital Vigor Model (DVM), K-means method for classification of UAS based RS images for different uses (Table 4).

SVM is classification technique widely used for detection of disparity, land, visitation (plants, crops), etc. (Javan *et al.*, 2019). Javan *et al.* (2019) have used SVM to detect non-tree space within a plantation (Citrus trees), healthy and diseased trees. Durfee *et al.* (2019) have used this technique for classification of vegetation over a watershed.

Point cloud technique was used for preparation of DEM using ERGBVE (Themistocleous, 2019). Point cloud data was used to acquire TIN structures of rice plots in Switzerland based on UAV data (Jiang *et al.*, 2019). This method was used for estimation of plant height for calculation of AGB of maize (Niu *et al.*, 2019). Park *et al.* (2019) have used statistical techniques: mean, median and standard deviation for detection of leaf cover of individual tree using RGB Chromatic Coordinates, excess green, green vegetation, non-photosynthetic indices, etc. Kerle *et al.* (2020) have showed applicability of 3D point clouds for highly detailed and accurate scene reconstruction to recognize the features.

Simple Linear Regression (SLR) was used of AGB of rice using multiple indices, TIN based structural feature of plots, meteorological data (Jiang *et al*., 2019). Simple Exponential Regression (SLR) was used of AGB of rice using multiple indices, TIN based structural feature of plots, meteorological data (Jiang *et al*., 2019).

Buchaillot *et al.* (2019) have reported better performance of multivariate regression models calculated based on RGB indices for estimations of agronomic parameters. Further, they have calculated grain Yield Loss Index (GYLI) for analysis of variability in crop productions. Fathipoor *et al.* (2019) have established Partial Least Squares Regression (PLSR) Model using plant height estimated using AUV-RGB based DEM for estimation of crop yield in Iran.

Jiang *et al.* (2019) have used Random Forest (RF) method for combing the UAV based MSS, structural and metrological data for estimation of AGB of rice crop. Wan *et al.* (2018) have used this technique for prediction of flower number using UAV-RGB data for oilseed rape. Oliveira *et al.* (2019) have reported better performance of RF than multiple linear regression calculated from RGB and hyperspectral datasets for estimation and validation of grass. Further, Digital Vigor Model (DVM) has been obtained from Digital Surface Model (DSM) and Digital Terrain Model (DTM) established base on AUV-RGB images (Vanegas *et al*., 2018). Wan *et al.* (2018) have used K-mean method for identification of flower coverage area of oilseed rape.

One-tailed Z-test was used to test the significance of relationship between VIs and study objects. Yeom *et al.* (2019) have conducted this test to find the significance of VIs difference with tillage and non-tillage treatment in agriculture.

Accuracy of estimated results has been achieved more than 95% using UAV remote sensing technique. Javan *et al.* (2019) have been detected and classified diseased Citrus trees at more than 95% accuracy.

Table 4. Estimation, Predictions and Classification techniques

Technique	Data	Authors	Applications
Simple Linear Regression (SLR)	RGB (3 bands) MSS (5 bands)	Li *et al*. (2019) Jiang *et al.* (2019)	Estimation of LAI using VIs. Estimation of plant based on using indices.
		Guo *et al.* (2019)	To calibrate the MSS images in little cloudy and cloudy weather.
Multiple Linear Regression (MLR)	RGB (3 bands)	Li *et al*. (2019)	Estimation of LAI using VIs.
Partial Least Squares Regression (PLSR)	RGB (3 bands)	Li *et al*. (2019)	Estimation of LAI using VIs.
Simple Exponential Regression (SER)	MSS (12 bands)	Jiang *et al.* (2019)	To estimate the AGB of rice crop.
Random Forest (RF)	RGB (3 bands)	Li *et al*. (2019)	Estimation of LAI using VIs.
Principal Component Regression (PCR)	RGB (3 bands)	Li *et al*. (2019)	Estimation of LAI using VIs.
Support Vector Machine (SVM)	MSS (5 bands)	Javan *et al.* (2019)	To detect the tree and non-tree objects. To detect the Greening disease of citrus trees.
		Li *et al*. (2019) Durfee *et al.* (2019)	Estimation of LAI using VIs. Canopy classification over a watershed.
Point Cloud	RGB (3 bands) MSS (5 bands)	Themistocleous (2019) Jiang *et al.* (2019)	To prepared the DEM. To estimate the TIN based structural aspects of the rice plots.
Universal Calibration Equation	MSS (6 bands)	Guo *et al.* (2019)	To calibrate the MSS images in little cloudy and cloudy weather.

4 FINDINGS AND CONCLUSIONS

1. The market revenue of UAS based remote sensing and mapping is bumming since last decade.
2. UAS based RS techniques are widely used for analysis of vegetation cover, agriculture, hydro-geomorphological aspects, hydrology, water conservation programs, water qualities, river characteristic as well as for soil management, urban mapping, disaster management, etc.
3. Timely, intensive, cost effective and efficient data collection with less labor and time can be possible using UAV systems (Yeom *et al.*, 2019).
4. UASs based RGB, MSS and hyperspectral datasets are available for analysis of biophysical parameters of the Earth surface.
5. MSS sensors more costly than the RGB sensors (Marcial-Pablo *et al.*, 2018).
6. Some studies have been conducted to analyze the impacts of changes in flight height on number of detected features and definition of ground truth information (Javan *et al.*, 2019). Image resolution varies according to the flying height.
7. UAS provides data at fine resolution (finer than 1cm) with desired temporal resolution.
8. The atmospheric distortions appear more in images with increasing flying height (Guo *et al.*, 2019).
9. Flying time affects the sun light and angle, weather, atmospheric transference, plant phenology.
10. Ground reflectance panel, ambient illumination sensors and mean DN values calculated using white reference were effectively used for calibration of UAV based sensing images.
11. The universal calibration equation is more suitable for calibration of images acquired sunny and little cloudy commissions (Guo *et al.*, 2019).
12. Normalized RGB bands were used before calculation of VIs in many research projects.
13. Image clarity and analytical preciseness are fully relied on geo-referencing of image captured using multi-leans sensors.
14. Several USA based RGB and NIR VIs have been used for different parameters of the Earth surface.
15. VIs is widely used for agricultural applications: leaf area estimations, canopy analysis, plant nutrients analysis (nitrogen status), biomass estimations, plant growth, crop yield estimations, etc.
16. VIs correlate with disease severity based on vegetation physiology status: tree leaves including biomass, leaf area, chlorophyll, water content, carotenoid content, anthocyanin content, etc. (Jansen *et al.*, 2014)
17. UAV-RGB based vegetation indices have great potential of high precision and low-cost assessment, planning and monitoring of agriculture, water resources, settlements, deserters, etc.
18. Normalized Green-Red Difference Index (NGRDI) is similar to NDVI and useful to analyze the vegetation covers.
19. Excess Red shows positive correlation with crop height estimated using DEM prepared based on AUV images.
20. RGB based ExG is best option for cost reduction for early season crop monitoring.
21. RGB based VIs and models are efficient for estimations of AGB (Niu *et al*., 2019).
22. ExG, CIVE and Vegetativen are useful for delineation of levels of green vegetation (Wan *et al.*, 2018).
23. NGRDI, RGRI and MGRVI show significant correlations with number of flowers of oilseeds (Wan *et al.*, 2018).
24. NIR based VIs are found more superior than RGB VIs to find precise vegetation differences (Yeom *et al.*, 2019).
25. UAV-based NDVI was used widely for vegetation analysis including forest classification, plant stress analysis, crop nutrient detection, crop/plant disease detection, etc.
26. NDVI is not able to distinguish the typical disease (viz. phylloxera infestation) stress in vegetation, therefore other sources and thermal imageries are suggested to overcome these limitations.
27. GNDVI shows stronger relation with drought stressed and non-stressed condition crops.
28. GNDVI is reported superior for analysis of vegetation fractions in cropping area (Marcial-Pablo *et al.*, 2018).
29. Combination of MSS and TIN based structural data gives more precise results than use of any data alone (Jiang *et al.*, 2019).
30. SLR, SER and RF are useful techniques for combining the UAV based data and indices with different type of data like TIN based structural features, meteorological data, etc. (Jiang *et al.*, 2019).
31. Similar performance was observed in case UAV base RGB VIs to ground based data for crop performance: crop yield (Gracia-Romero *et al.*, 2019).
32. Support Vector Machine (SVM), Point Cloud, Simple Linear Regression (SLR), Simple Exponential Regression, Random Forest (RF), Partial Least Squares Regression (PLSR) Model, Digital Vigor Model (DVM), K-means are the method for classification of UAS based RS images for different uses.

Limitations of the UAV systems are: limited coverage and battery, flight limitations in windy weather, safety problems, (Yeom *et al.*, 2019), higher initial costs, sensor capability, image processing and final products dissemination (Zhang and Kovacs, 2012). Image distortions from camera and environmental factors are weakening the applicability of the UAV RS techniques (Holman *et al*., 2019).

No significant improvement was found in correlation of VIs with AGB in multivariable linear regression model (Niu *et al*., 2019). They have suggested machine learning techniques for better estimations. VIs base vegetation status analysis does not allow differentiation between the diseases (Jansen *et al*., 2014). Therefore, disease specific indices can be helpful for identification of crop disease and detection and delineation of diseased area.

All UAS based VIs calculated and used for different analysis of earth surface are tested in small area and results are very site-specific. Results of used methods, techniques and datasets can be changed according to biophysical environment. Therefore, UAS-VIs should be calculated using multiple datasets captured at different biophysical environmental conditions for successful application of the results (Sandino *et al*., 2018; Jiang *et al*., 2019). UAV based RGB and MSS combined cameras will more promising for vegetation analysis for planning and monitoring the forestry and agriculture (Wan *et al.*, 2018). The technology is promising and will grow exponentially in coming years (Sankaran *et al*., 2015).

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

ABBREVIATIONS

AGB: Above Ground Biomass; **B**: Blue; **CI**: Chlorophyll Index; **DEM**: Digital Elevation Model; **DN**: Digital Number; **EGMER**: Excess Green Minus Excess Red; **ERGI**: Enhanced Red-Green-Blue; **G**: Green; **GCP**: Ground Control Point; **GCS**: Ground Control Station; **GI**: Greenness index; **GLI**: Green Leaf Index; **GRVI**: Green Ratio Vegetation Index; **G-RVI**: Green-Red Vegetation Index; **IPVI**: Infrared Percentage Vegetation Index; **MCARI**: Modified Chlorophyll Absorption in Reflectance Index; **MRENDVI**: Modified Red Edge Normalized Difference Vegetation Index; **MRESR**: Modified Red Edge Simple Ratio; **MSS**: Multispectral Scanner System; **MTVI1**: Modified Triangular Vegetation Index-1; **MTVI2**: Modified Triangular Vegetation Index-2; **NDVI**: Normalized Difference Vegetation Index; **NEGI**: Normalized Excess Green Index; **NGDVI**: Normalized Green Difference Vegetation Index; **NG-RDI**: Normalized Green-Red Difference Index; **R**: Red; **RENDVI**: Red Edge Normalized Difference Vegetation Index; **RGB**: Red Green Blue; **RGBVI**: Red-Green-Blue Vegetation Index; **RNDVI**: Renormalized Difference Vegetation Index; **RPAS**: Remotely-Piloted Aerial Systems; **SIPI**: Structure Insensitive Pigment Index; **SR**: Simple Ratio; **SVM**: Support Vector Machine; **TVI**: Triangular Vegetation Index; **UAS**: Unmanned Aircraft Systems; **UAV**: Unmanned Aerial Vehicle; **VARI**: Visible Atmospherically Resistant Index; **VI**: Vegetation Index; **VIEG**: Vegetation Index of Excess Green.

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