



GEOSCIENCES

Seasonal behavior of vegetation determined by sensor on an unmanned aerial vehicle

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Abstract: Geographic information systems make it possible to obtain fine scale maps for environmental monitoring from airborne sensors on aerial platforms, such as unmanned aerial vehicles (UAVs), which offer products with low costs and high space-time resolution. The present study assessed the performance of an UAV in the evaluation of the seasonal behavior of five vegetation coverages: *Coffea* spp., *Eucalyptus* spp., *Pinus* spp. and two forest remnants. For this, vegetation indices (Excess Green and Excess Red minus Green), meteorological data and moisture of surface soils were used. In addition, Sentinel-2 satellite images were used to validate these results. The highest correlations with soil moisture were found in coffee and Forest Remnant 1. The *Coffea* spp. had the indices with the highest correlation to the studied soil properties. However, the UAV images also provided relevant results for understanding the dynamics of forest remnants. The Excess Green index ($p = 0.96$) had the highest correlation coefficients for *Coffea* spp., while the Excess Red minus Green index was the best index for forest remnants ($p = 0.75$). The results confirmed that low-cost UAVs have the potential to be used as a support tool for phenological studies and can also validate satellite-derived data.

Key words: *Coffea* spp., *Eucalyptus* spp., Forest Remnants, *Pinus* spp., vegetation Indices.

INTRODUCTION

Unmanned aerial vehicles (UAVs) have dynamized Earth's surface studies by collecting data at low altitudes (Getzin et al. 2012). The combination of these platforms with computer vision algorithms ensures the generation of high-quality products, such as orthophotomosaics and three-dimensional (3D) models, which have the potential to detect and identify wildlife and flora classes. These parameters are difficult to distinguish using conventional platforms (Franke et al. 2012, Vermeulen et al. 2013, Zhang et al. 2014). Thus, UAVs represent an important tool in agro-environmental studies, considering the imminent needs for conserving

natural resources and promoting food security (Anderson & Gaston 2013, Koh & Wich 2012).

In this scenario, these platforms appear to be a potential new option for monitoring vegetation phenology (Zeng et al. 2020, Klosterman et al. 2018, Dandois & Ellis 2013) since they offer new opportunities for the scale-appropriate measurement of ecological phenomena, delivering fine spatial resolution data at user-controlled revisiting periods with relatively low cost (Hardin et al. 2019, Anderson & Gaston 2013). In addition, UAVs allow the assessment of vegetation structure, such as the detection and monitoring of natural gaps and species identification for forest inventory and agricultural mapping by vegetation indices (Beniaich et al. 2019, Wallace et al. 2016, Jorge et

al. 2014, Raymond et al. 2011, Ferrier & Drielsma 2010). This information is relevant to maximize yields and adjust conservation practices (Bendig et al. 2015, Croft et al. 2014, Torres-Sánchez et al. 2013).

Several studies have applied sensors onboard UAVs to obtain time series data in seasonal vegetation patterns (Klosterman et al. 2018, Klosterman & Richardson 2017, Berra et al. 2016), which can be justified by the fact that the collection of this information is similar to the operations of satellite sensors but at low altitudes (Zeng et al. 2020, Zhang et al. 2017). Therefore, UAV time series can be useful for fine-scale measurements of vegetation phenology as well as satellite-based product validation (Klosterman et al. 2018).

However, a few studies have shown that these data are not being properly validated (Berra et al. 2019), and one of the main challenges in multitemporal studies is still the radiometric calibration of UAV imagery (Berra et al. 2017). Therefore, despite the potential of UAVs to fill the gap between the spatial resolution of satellites and the field scale (Pineux et al. 2017), monitoring large areas remains a significant challenge (Hufkens et al. 2012, Morris et al. 2013).

Thus, overcoming these limitations is a way of strengthening not only the monitoring of the landscape by UAVs but also contributing to reducing the worldwide loss of remaining forests and managing and conserving ecosystems. According to the FAO (2018), dominant trends of deforestation persist, and forested areas have decreased 130 million ha worldwide in the last 25 years.

In this context, this study aimed to (i) validate the performance of a RGB sensor carried on a low-cost multicopter UAV for the seasonal study of vegetation and (ii) assess the potential for the use of UAV imagery to validate satellite-derived data. For these objectives, two

vegetation indices were utilized: (i) Excess Green and (ii) Excess Red minus Green, in addition to superficial soil samples (0 - 20 cm) and Sentinel-2 satellite images.

MATERIALS AND METHODS

Study area

The study area is located in the municipality of Lavras State of Minas Gerais (Figure 1).

Forest Remnant 1 has the largest area (5.8 ha) and has the highest diversity index (Shannon - $H' = 3.90$), and it is characterized by a flat topography and an open canopy of approximately 15 m. There are several natural gaps, and the most representative species are *Copaifera langsdorfii*, *Xylopia brasiliensis*, *Sclerolobium rugosum*, *Ocotea corymbosa*, *Cryptocarya aschersoniana*, *Tapirira obtusa* and *Ocotea odorifera* (Aubert & Oliveira-Filho 1994). Forest Remnant 2 is smaller (2.81 ha) and has a typical Cerrado (Savanna) physiognomy. This area has 19 families, 38 species, and 38 genera ($H' = 3.28$), with the exclusive occurrence of individuals such as *Bowdichia virgiloides*, *Dalbergia miscolodium*, and *Qualea grandiflora* (Pereira et al. 2010).

The areas dominated by *Pinus* spp. and *Eucalyptus* spp. are composed of old homogeneous plantations with mature undergrowth. These areas are strongly influenced by the surrounding forest remnants since they represent their connecting units. In addition, they have been severely impacted by fires (Pereira et al. 2010, Aubert & Oliveira-Filho 1994).

The coffee area has a slight declivity of 12% with leveled planting, and crop management makes use of mulching by covering the soil with grass and the implementation of minimum tillage, which creates protective conditions

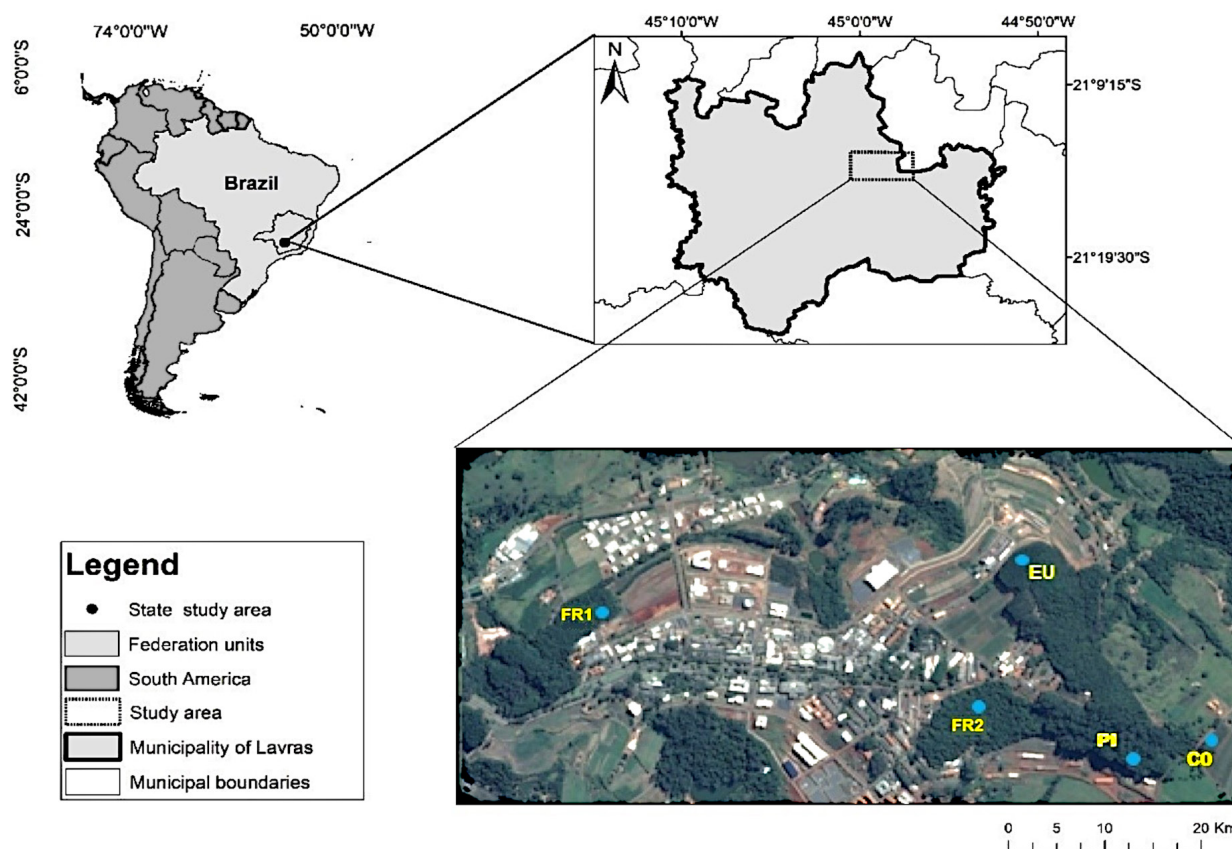


Figure 1. Location map of the study area with the demarcation of the coverages studied in the municipality of Lavras, south of Minas Gerais. FR1: Forest Remnant 1; FR2: Forest Remnant 2; EU: *Eucalyptus* spp., PI: *Pinus* spp. and CO: *Coffea* spp.

against erosion and superficial rainfall runoffs (V.L. Naves et al., unpublished data).

According to the Köppen classification system, the climate of the study area is mesothermal tropical (Cwb) (Sparovek et al. 2007). The average elevation is 918 m and the mean annual precipitation is 1529.7 mm, and all soils are classified as dystroferric Red Latosols, characterized by a clayed texture, a deep extent and a high level of Fe₂O₃, MnO and TiO₂ (FEAM 2010).

The region is part of the upstream portion of the Rio Grande watershed and makes up the geomorphological Atlantic Plateau unit with rolling relief in Varginha Complex crystalline rocks (Pinto & Silva 2014). The vegetation is

characterized by the transition of the Atlantic Forest to the Cerrado (Savanna), with the presence of the remnants of Montana Semi Deciduous Forest in the Atlantic Forest domain (Oliveira-Filho et al. 2001).

Procedure

The research was organized into five stages (Figure 2).

Unmanned aerial vehicle (UAV)

In the first stage, we used the UAV Phantom 3 (Professional) with a RGB sensor, camera model Sony EXMOR 1/2.3", which captures images in real color with lens 94° FOV 20 mm.

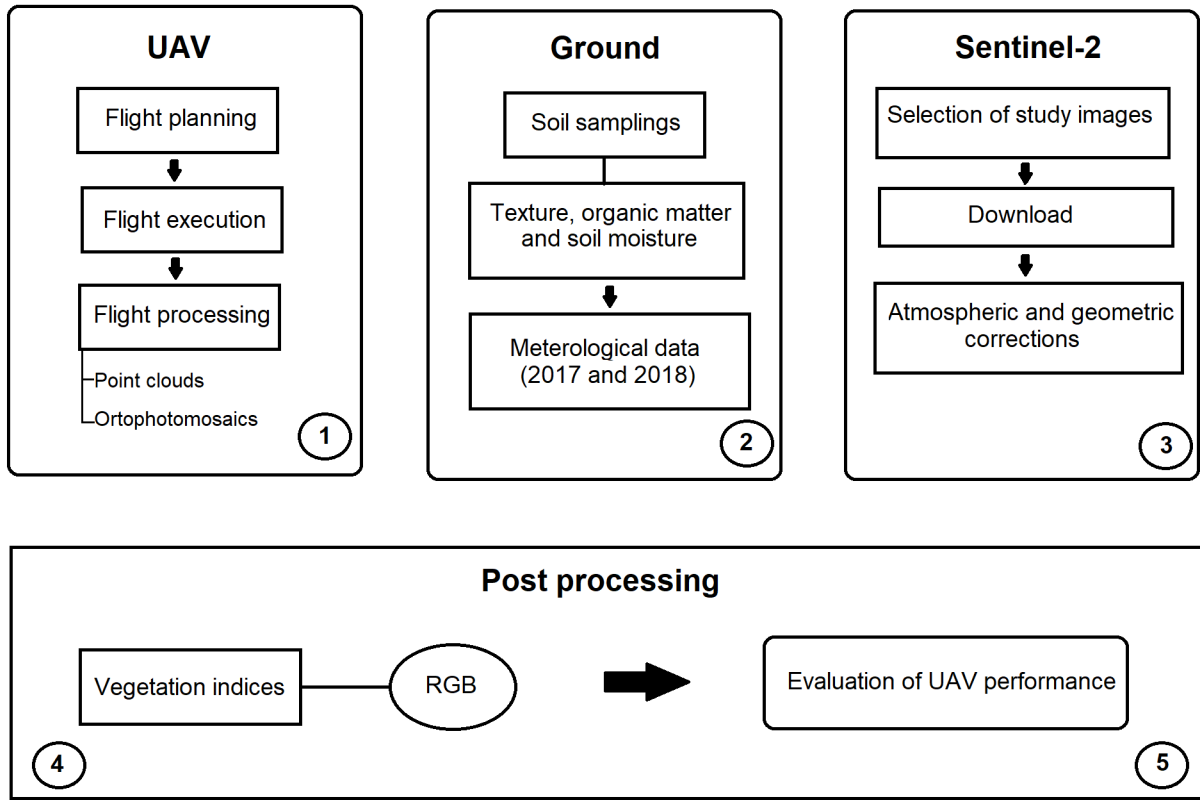


Figure 2. Flowchart with the five stages of study development: (1) Mapping with UAV; (2) Field sampling; (3) Obtaining and correction of Sentinel-2 images; (4) Application of vegetation indices and (5) results.

Flights were scheduled to run in the middle of each season (2017-2018) to detect seasonal patterns at a height of 60 m and with 80% forward and side overlap. Two grids were adopted: a 50 x 50 m in the remaining forests and another 100 x 50 m in the areas containing *Coffea* spp., *Pinus* spp. and *Eucalyptus*. Mapping of the areas was conducted from 20 autonomous flights that were planned and executed using the Pix4DCapture software.

The images were processed using the commercially available structure-from-motion (SfM) Agisoft Photoscan Professional® v1.2.7 software. A reconstructed mesh surface was derived from the point cloud by using the automatic classification of points procedure based on (i) max angle, (ii) max distance, and

(iii) cell size (Panagiotidis et al. 2017). No ground control points (GCPs) were used for image orthorectification.

Satellite

The Sentinel-2 images in Level-2 were obtained from the Earth Explorer portal (USGS), which has a resolution of 10 m in the visible spectrum, processed using the SNAP 2.5 (Sentinels Application Platform) software for atmospheric, terrain and reflectance correction through the sen2cor tool. The dates, sun elevation and sun azimuth for the Sentinel imagery are in Table I. Images from April and June were not analyzed due to the presence of clouds.

Table I. Date, sun zenith angle mean, sun elevation and sun azimuth angle mean of satellite Sentinel-2.

Date	Sun zenith angle mean	Sun elevation	Sun azimuth angle mean
Autumn			
05/02/2017	44.31	45.69	35.83
Winter			
07/01/2017	51.51	38.49	32.09
07/21/2017	49.57	40.43	34.64
07/26/2017	-	-	-
08/15/2017	-	-	-
08/30/2017	39.48	50.52	42.99
09/04/2017	-	-	-
09/19/2017	32.78	57.22	49.51
Spring			
09/24/2017	-	-	-
10/09/2017	26.49	63.51	59.25
10/14/2017	25.20	64.80	62.44
11/13/2017	20.96	69.04	85.09
Summer			
12/28/2017	23.54	66.46	99.55
01/22/2018	27.02	62.98	91.62
02/16/2018	29.53	60.47	76.08

Ground truth

In the field study (stage 3), georeferenced samples were collected from the soil surface (0 - 20 cm) in five areas using a GPS model: GARMIN eTrex Vista H.

A previous pilot study was carried out to determine the representative number of soil samples needed to conduct the research. Thus, 250 surface layer soil samples for each cover were collected from transects in autumn with

50 samples from each covering; it was possible to determine from regression, using weather station data, that 10 samples from each cover type were significant.

Soil sampling campaigns were carried out on the same day as the flights with the collection of 50 samples for organic matter, texture and moisture analysis. However, because coffee harvesting during the summer occurred days before collection, it was not possible to study this vegetation cover in this particular season.

Sampling was carried out randomly along the flight grids. The organic matter was determined by the volumetric method with potassium dichromate (EMBRAPA 1998), while the soil texture was obtained by the densitometer method (Black 1986). The standard moisture was measured by the gravimetric method (Hillel 1998), and field measurements were carried out for soil moisture and temperature using sensor reflectometry (Time Domain Reflectometry, TDR - 5, TM Decagon Devices). Principal component analysis (PCA) was conducted to investigate the relationship between soil attributes and coverages.

To assess the seasonality of the vegetation indices, climate information, such as temperature, mean rainfall, and insolation, were obtained from a climatological station located in Lavras from January 2017 to March 2018.

Vegetation indices

The vegetation indices Excess Green (Woebbecke et al. 1995) (Equation 1) and Excess Red minus Green (Meyer & Neto 2008) (Equation 2) were tested in stage 4 using ArcGIS 10.4.1 (Esri 2017).

$$ExG = (2 * (\text{green}) - (\text{red}) - (\text{blue})) \tag{1}$$

$$ExRmG = (2 * (\text{green}) - (\text{red})) - (1.4 * (\text{red}) - (\text{green})) \tag{2}$$

These vegetation indices were selected according to Torres-Sánchez et al. (2013) and

Saberioon et al. (2014) who assessed their accuracy with UAVs and presented relevant results. As the aim of this study was to evaluate the potential of low-cost tools based on RGB sensors, indices that had already presented results in similar study applications were chosen (Rasmussen et al. 2016, Beniaich et al. 2019, Zheng et al. 2020). Considering that these indices seek to enhance the influence of vegetation and reduce that of soil, they were suitable for this study's goals.

The mean value of each vegetation index was extracted from polygons delimited according to the soil sample points georeferenced on the ground, and the threshold scope of the samples under each cover was determined. The orientation of this process was based on three vectors: the translation vector "t", the rotation vector "r" and the vector of size "s", which were accessed from elements addressed with the x, y and z suffixes (Esri 2017) (see Supplementary Material - Appendix S1 (Tables SI, SII and Figure S1)). Posteriorly, a mesh of 10 x 10 m was created, a dimension similar to the spatial resolution of the Sentinel-2 images, to extract the mean values from each vegetation index. This procedure minimized the differences due to the different spatial resolutions of these platforms.

Mean values for the cells of each mesh were obtained from a table by considering the number of pixels in the polygons and its maximum, medium and minimum values as well as the sum and standard deviation. The values used for the study are the means for each polygon.

To normalize the orthophotomosaics, Flight 1 (05/02/2017) was used as a reference. Thus, common targets with no significant variation in reflectance were identified among all orthophotomosaics of vegetation indices. Therefore, targets were mainly selected from exposed soil, roofing and asphalt and are represented by a circular geometry of varied

sizes. Upon the detection of these areas, the mean values for each were determined using the same methodology adopted in the extraction of vegetation indices, and these values were subjected to a linear regression. Therefore, these equations were applied on the orthophotomosaics for final calibration, and the R² illustrates the procedure effectivity (Table II).

The extraction method of the mean values of each vegetation index in the Sentinel-2 images was similar to the aforementioned methods. Thus, in stage 5, means were analyzed by Pearson's correlation using the data obtained from both platforms to determine the best performance rate in each cover.

Table II. Equations applied to normalize orthophotomosaics per cover.

Cover	Equation	R ²
ExG		
Coffea spp.	y = 1.0631*MEAN + 8.3589	0.93
	y = 0.8444*MEAN + 26.545	0.99
FR1	y = -0.2487*MEAN - 22.449	0.14
	y = -0.2539*MEAN - 11.256	0.10
	y = -0.5918*MEAN - 18.31	0.36
FR2	y = -0.2335*MEAN - 21.952	0.14
	y = -0.3339*MEAN - 12.852	0.14
	y = -0.6766*MEAN - 19.608	0.48
ExRmG		
Coffea spp.	y = 0.9409*MEAN - 64.895	0.83
	y = 0.8978*MEAN - 26.023	0.88
FR1	y = 0.4662*MEAN - 322.15	0.76
	y = 0.566*MEAN - 277.13	0.78
	y = 0.6077*MEAN - 237.1	0.76
FR2	y = 0.4824*MEAN - 319.26	0.77
	y = 0.5804*MEAN - 271.74	0.74
	y = 0.6184*MEAN - 232.34	0.73

ExG: Excess Green; ExRmG: Excess Red minus Green; FR1: Forest Remnant 1 and FR2: Forest Remnant 2.

RESULTS

Ground analysis

A total of 190 soil samples were collected for the PCA. The PCA results (Figure 3) showed a high correlation between the soil attributes and coverages, suggesting that the vegetation type is considered a soil property indicator.

As observed in Figure 3, the cover type that showed the strongest association with soil moisture were *Coffea* spp. and Forest Remnant 1; these were expected to have the highest correlation to the proposed vegetation indices.

Table III presents the variability of moisture and temperature for each coverage per season, which were similar between each areas, except

for the *Eucalyptus* spp., while Figure 4 shows the variability of climatic data in 2017 and 2018.

Orthophotomosaics

Regarding the orthophotomosaics, *Pinus* spp. and *Eucalyptus* spp. areas have not been evaluated by UAV due to the difficulty of these platforms in mapping homogeneous coverings (Matese et al. 2015, Pádua et al. 2017) formed by vegetal clones. Another factor that may also justify this shortcoming was flying altitudes: because tests were performed at an altitude up to 110 m they did not provide satisfactory results, likely due to the morphology of the small leaves (Matese et al. 2015).

However, in other areas, the aerial surveys reached 2 cm spatial resolution (mean value)

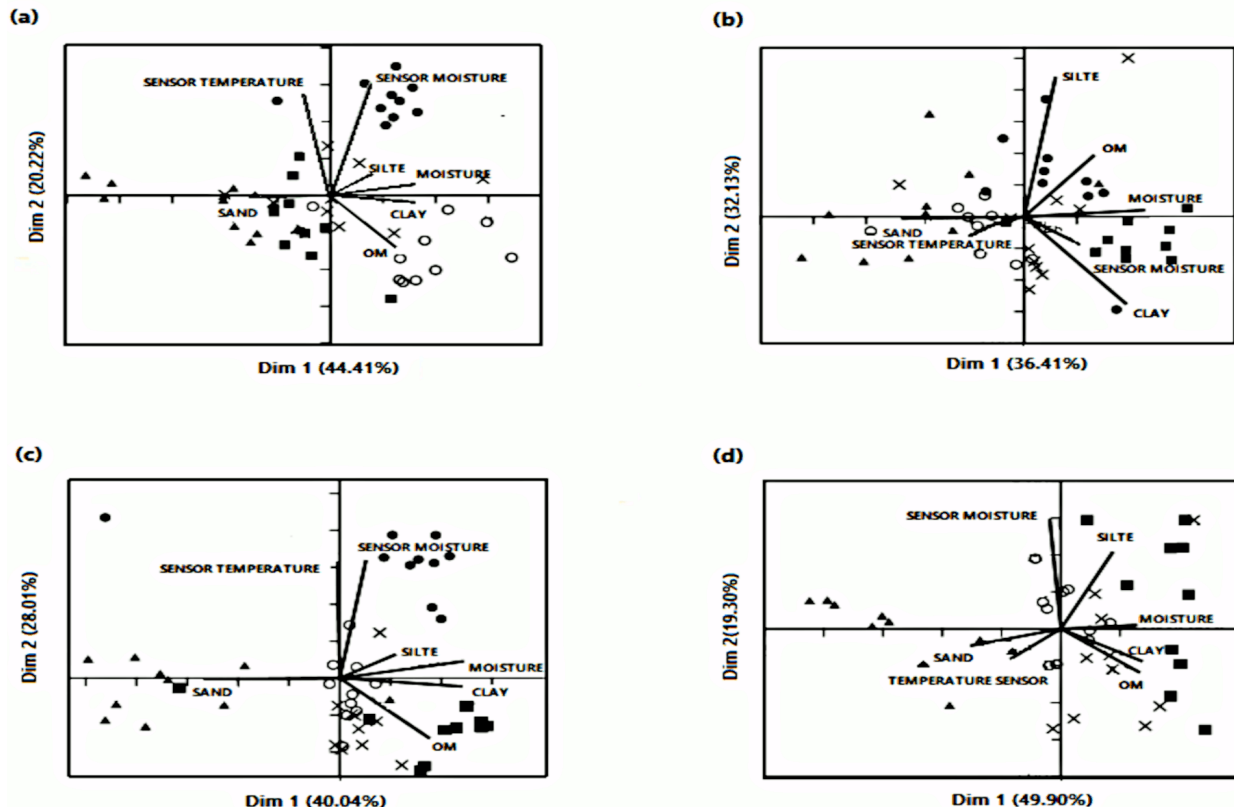


Figure 3. Principal component analysis (PCA) of cover and soil properties. It is possible to detect that the soil moisture variability of *Pinus* spp. was similar to Forest Remnant 1 and Forest Remnant 2. (a) Autumn, (b) winter, (c) spring and (d) summer. Filled circle: *Coffea* spp., Triangle: *Eucalyptus* spp., X: *Pinus* spp., Open circle: FR1 and Square: FR2. OM: Organic matter.

and allowed the detection and individualization of natural gaps and trees. (Figure 5).

Vegetation indices

The mean values of each vegetation index per season (Table IV) represents seasonal variability and highlights the differences between the two platforms, although they both indicated similar correlation between vegetation dynamics and soil moisture (Figure 6, Table V and Table VI).

The index with the highest correlation to *Coffea* spp. was Excess Green ($p = 0.96$), although

Excess Red minus Green also performed well ($p = 0.94$). Regarding the forest remnants, highest correlation was in Forest Remnant 1 with the Excess Red minus Green index ($p = 0.75$), while this relationship for Forest Remnant 2 was not as high ($p = 0.37$). The Excess Green index ($p = - 0.29$ and $p = - 0.30$) was similar for both coverings and did not perform well.

Table III. Mean values and standard deviation of soil moisture and temperature.

Season	Date	SM	ST
		%	°C
<i>Coffea</i> spp.			
Autumn	May 2nd, 2017	32.08 (1.89)	22.05 (1.06)
Winter	August 24th, 2017	24.99 (2.36)	23.69 (2.46)
Spring	November 23rd, 2017	32.11 (2.63)	24.74 (1.73)
Summer	January 30th, 2018	-	-
FR1			
Autumn	May 2nd, 2017	25.15 (1.46)	19.35 (1.80)
Winter	August 24th, 2017	22.51 (2.61)	23.62 (0.89)
Spring	November 23rd, 2017	31.59 (1.54)	21.3 (0.49)
Summer	January 30th, 2018	34.19 (1.32)	23.6 (0.63)
FR2			
Autumn	May 2nd, 2017	30.92 (6.39)	18.19 (1.00)
Winter	August 24th, 2017	28.27 (2.63)	22.45 (1.02)
Spring	November 23rd, 2017	33.02 (2.38)	21.24 (0.34)
Summer	January 30th, 2018	33.81 (4.30)	23.03 (0.52)
<i>Pinus</i> spp.			
Autumn	May 2nd, 2017	27.26 (4.61)	21.00 (0.96)
Winter	August 24th, 2017	23.11 (1.70)	20.13 (2.06)
Spring	November 23rd, 2017	31.16 (0.62)	21.06 (0.38)
Summer	January 30th, 2018	32.96 (1.68)	22.95 (0.70)
<i>Eucalyptus</i> spp.			
Autumn	May 2nd, 2017	19.44 (2.76)	21.50 (0.60)
Winter	August 24th, 2017	18.93 (1.95)	23.79 (1.23)
Spring	November 23rd, 2017	22.57 (3.97)	22.02 (0.46)
Summer	January 30th, 2018	25.01 (5.20)	23.84 (0.38)

SM: Soil Moisture; ST: Soil Temperature; FR1: Forest Remnant 1 and FR2: Forest Remnant 2.

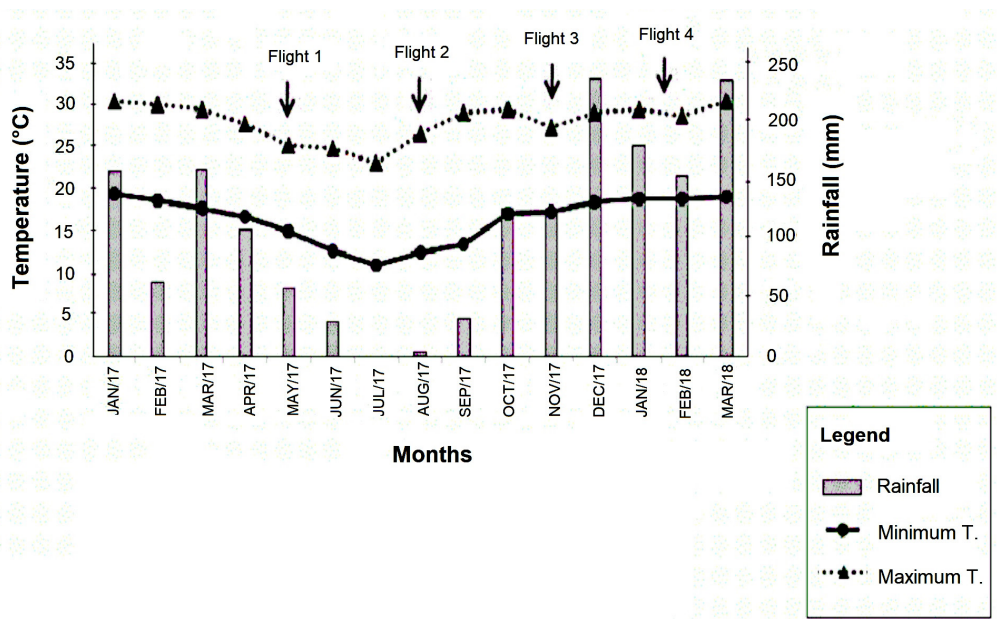


Figure 4. Climatic variables and flight in the study period (2017/2018).

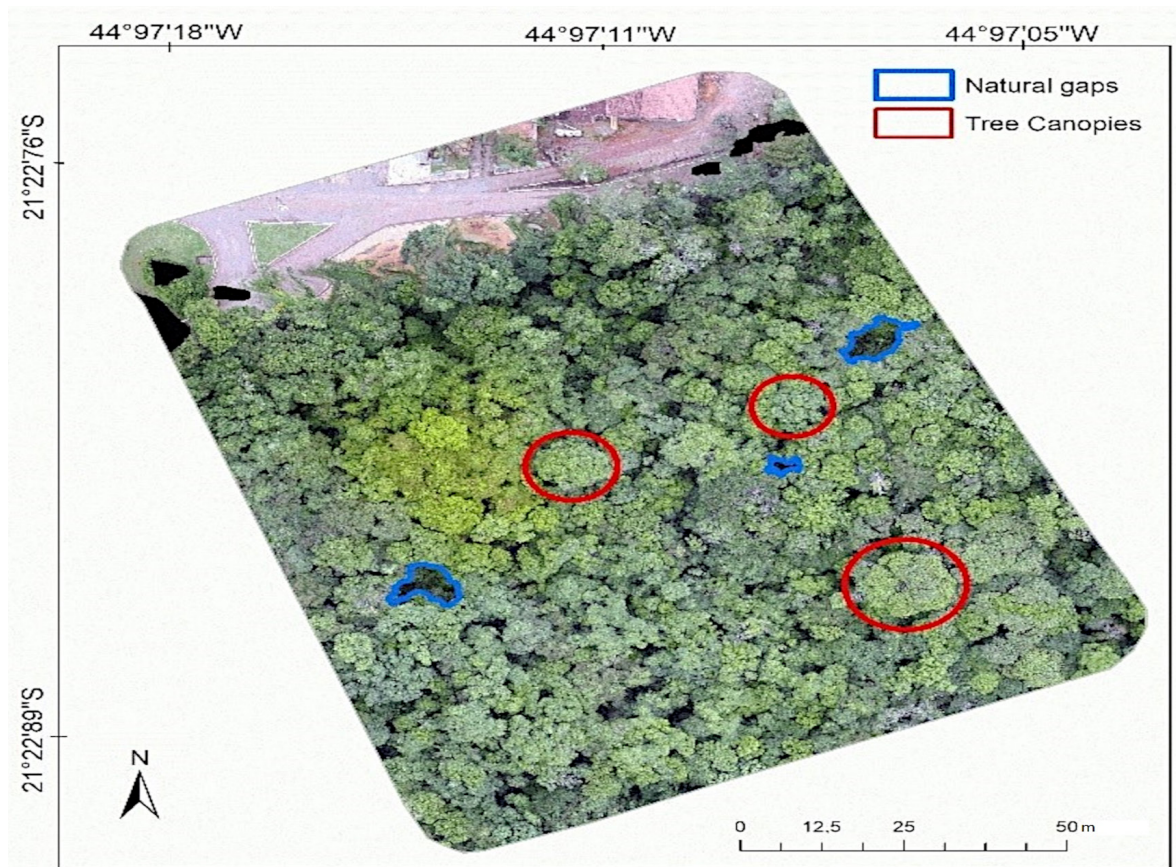


Figure 5. The aerial surveys allowed the detection of natural gaps and trees, which are necessary data for the sustainable management and ecological stability of these areas. In this orthophotomosaic of Forest Remnant 2 in the summer, the tree canopies are indicated in red and natural gaps in blue.

Table IV. Mean values of vegetation indices across seasons of 2017/2018.

Vegetation Indices	Season							
	Autumn		Winter		Spring		Summer	
	UAV	S-2	UAV	S-2	UAV	S-2	UAV	S-2
ExG								
<i>Coffea</i> spp.	44.04	37.70	-05.74	109.00	77.11	63.00	-	-
FR1	-12.20	85.50	-24.16	70.85	13.46	183.30	-29.21	214.00
FR2	78.00	77.34	62.00	12.00	96.86	156.6	45.03	217.44
<i>Pinus</i> spp.	-	100.85	-	15.37	-	64.53	-	199.00
<i>Eucalyptus</i> spp.	-	22.03	-	-	-	12.68	-	98.27
ExRmG								
<i>Coffea</i> spp.	-49.87	-168.92	-157.26	-211.09	10.49	-167.90	-	-
FR1	-225.24	-131.90	- 464.00	-133.36	-350.37	-131.72	-241.30	-103.30
FR2	-206.80	-121.49	-286.24	-156.57	-234.50	-122.16	-241.30	-98.57
<i>Pinus</i> spp.	-	-128.01	-	-147.54	-	-146.34	-	-110.58
<i>Eucalyptus</i> spp.	-	-129.37	-	-	-	-139.79	-	-107.27

ExG: Excess Green; ExRmG: Excess Red minus Green; UAV: Unmanned Aerial Vehicle; S-2: Sentinel-2; FR1: Forest Remnant 1 and FR2: Forest Remnant 2.

DISCUSSION AND CONCLUSION

The results obtained in this study are noteworthy because the vegetation indices indicated the correlation between vegetation dynamics and soil moisture, i.e., that the availability of moisture is related to evapotranspiration. This facilitates the understanding of the behavior of different vegetable covers in the regional climatic extremes.

The strong associations between meteorological data and vegetation indices are illustrated in Figure 4 and Table IV. In the autumn and summer, during periods of high rainfall and low sunlight, the values were larger and smaller, respectively, than the vegetation indices in other seasons. In winter and spring,

the index standards were opposite, explained by the fact that there is a considerable loss of leaves in this period, which adversely affects the spectral response (Ponzoni et al. 2015).

The coffee crop presented the highest correlation, validating the proposed methodology of the research, which leads to important applications of UAV for precision agriculture studies, especially south of the Minas Gerais State (Silva & Alves 2013). These results can be expanded to other areas of agricultural interest, and the vegetation indices can contribute to monitoring coffee production on a regional scale. Jeger & Pautasso (2008) and Khanal et al. (2017) also yielded promising results for monitoring soil moisture from UAVs, although these authors employed more robust

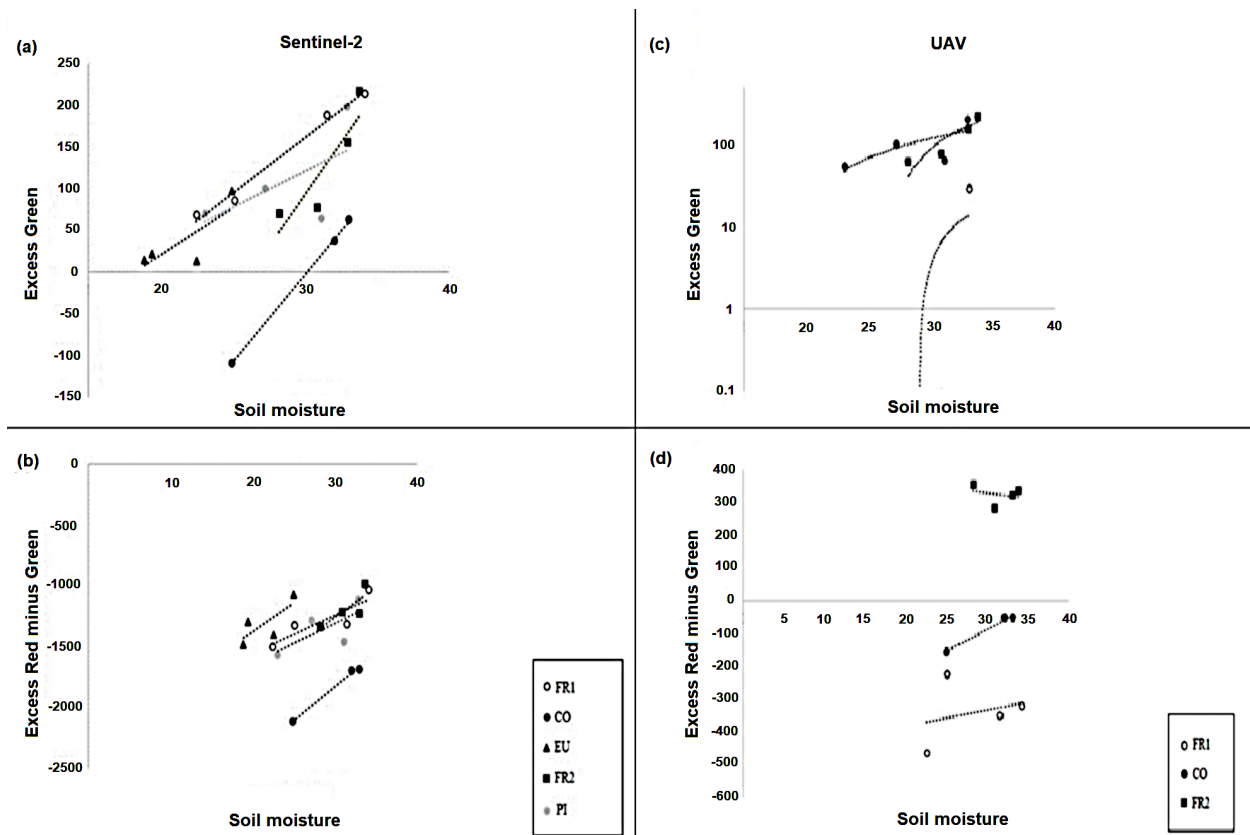


Figure 6. Correlation between soil moisture and vegetation indices obtained by the Sentinel-2 and UAV images. (a) Excess Green from Sentinel-2, with the *Pinus* spp. and *Eucalyptus* spp. showing lower correlation in relation to the others; (b) Excess Red minus Green from Sentinel-2, the persistence of the low correlation of *Pinus* spp. and *Eucalyptus* spp.; (c) Excess Green from UAV, the better correlation of *Coffea* spp.; (d) Excess Red minus Green, the vegetation index that showed the highest correlation to Forest Remnant 2, although presented the best answer in *Coffea* spp. FR1: Forest Remnant 1; CO: *Coffea* spp.; EU: *Eucalyptus* spp.; FR2: Forest Remnant 2 and PI: *Pinus* spp.

sensors with mid-infrared channels. Thus, the results of this study are also interesting since they allow the collection of consistent data from platforms with less sensitive sensors and can also contribute to the progress in coffee production. In this scenario, these platforms could contribute to the development of technologies that improve and standardize the local farming techniques, which are still very heterogeneous with different cultivation methods, sizes and management practices of cultivated areas.

Although native remnants have a higher correlation with soil moisture (Figure 3), this was not observed in the vegetation indices. This fact

may be explained by the effect of anthropogenic disturbances which are capable of affecting the spectral response of the vegetation (Pawar et al. 2014, Silveira et al. 2019). This was confirmed by observing the results of Forest Remnant 2, located in a highly anthropized region with roads, trails, constructions and technogenic deposits (inside and on the edges of the remnants) (Pereira et al. 2010), which reported a less significant correlation when compared to Forest Remnant 1, which is located in a slightly more isolated area, and *Coffea* spp. (Figure 1). Another critical point to consider is if this anthropization reflects the heterogeneity of the natural conditions of the Cerrado (Savanna)

Table V. Correlation between soil moisture and vegetation indices obtained by the Sentinel-2 images.

Sentinel-2	Linear regression	R ²
ExG		
<i>Coffea</i> spp.	$y = 20.986x - 633.55$	0.99
FR1	$y = 25.197x - 663.26$	0.80
FR2	$y = 13.265x - 237.17$	0.98
<i>Pinus</i> spp.	$y = 8.6473x - 138.65$	0.37
<i>Eucalyptus</i> spp.	$y = 11.331x - 206.38$	0.62
ExRmG		
<i>Coffea</i> spp.	$y = 55.494x - 3494.6$	0.99
FR1	$y = 48.989x - 2732.4$	0.69
FR2	$y = 30.437x - 2154.5$	0.75
<i>Pinus</i> spp.	$y = 32.448x - 2282.6$	0.49
<i>Eucalyptus</i> spp.	$y = 46.495x - 2309$	0.57

ExG: Excess Green; ExRmG: Excess Red minus Green; FR1: Forest Remnant 1 and FR2: Forest Remnant 2.

remnants in the state of Minas Gerais (Scolforo et al. 2015).

Conversely, the orthophotomosaics showed great potential to help understand the remnant’s dynamics. The aerial surveys allowed the detection of natural gaps and the individualization of the trees (Figure 5) which are necessary data to inform the sustainable management to ensure the ecological stability of these forest remnants as they influence the composition, distribution, and species richness and promote natural regeneration (Burton et al. 2014, Ward et al. 2018). Other studies have also implemented the use of UAVs to evaluate these forest attributes and confirmed the potential use of these platforms in collecting rapid, cheap and accurate data at different scales (Getzin et al. 2014, Chianucci et al. 2016), which are not compatible with conventional aerial or satellite imagery as the spatial resolutions of these data traditionally are inherently coarse and contain pixels with mixed cover (Herrmann & Tappan 2013).

It should be noted that the Cerrado (Savanna) represents a vital type of dryland and supports abundant wildlife and large human populations. In the state of Minas Gerais, this biome occupies approximately 33 million ha (Scolforo et al. 2015), and the deforestation rate is currently approximately 1.6% per year (Arantes et al. 2016) which has already affected more than 40% of the original area of this biome (Sano et al. 2010, Lathuillière et al. 2016). Thus, these results also confirm that the use of high precision tools, such as UAVs, can contribute to planning the conservation and maintenance of the Cerrado (Savanna) remnants, which are highly threatened by the conversion of native vegetation into agricultural areas.

Therefore, the response of vegetation cover to soil moisture and climatic variables has been confirmed, despite the areas of *Pinus* spp. and *Eucalyptus* spp. having not been monitored by the UAV due to homogeneities of these stands. The results of the Excess Green and Excess Red minus Green indices obtained with the Sentinel-2 also did not provide valid results, even

Table VI. Correlation between soil moisture and vegetation indices obtained by the UAV images.

UAV	Linear regression	R ²
ExG		
<i>Coffea</i> spp.	$y = 3.6071x - 104.94$	0.51
FR1	$y = 26.737x - 713.86$	0.84
FR2	$y = 10.212x - 187.3$	0.46
ExRmG		
<i>Coffea</i> spp.	$y = 13.632x - 496.29$	0.98
FR1	$y = -2.7811x + 411.08$	0.05
FR2	$y = 4.851x - 477.84$	0.07

ExG: Excess Green; ExRmG: Excess Red minus Green; FR1: Forest Remnant 1 and FR2: Forest Remnant 2.

with the soil moisture variability of *Pinus* spp. being similar to that of Forest Remnant 1 and Forest Remnant 2. However, for future research aimed at the specific mapping of *Pinus* spp. and *Eucalyptus* spp., the results are relevant because it enabled the recommendation of higher flight altitudes than those tested.

Last, the contribution of this study is to corroborate the feasibility of UAV and free satellite images as a low-cost alternative for seasonal monitoring of natural and planted vegetable coverings, with potential to have positive impacts on precision agriculture and the conservation and maintenance of forest remnants.

This proposal was not to compare the performance of the two platforms but to validate the potential of UAVs for studies on vegetation cover. The results confirm that, despite the spatial resolution being a differential of the UAVs in local analyses, satellites are still a steadier alternative to access the seasonality of different vegetation types on a regional scale. However, this does not prevent the integrated use of these platforms in agri-environmental research.

Thus, the conclusions of this research are as follows:

- 1) Vegetation indices derived from sensors onboard unmanned aerial vehicles were effective in the seasonal monitoring of vegetation and affirmed the application of this work in precision agriculture for *Coffea* spp.
- 2) Monitoring the conservation and management of forest remnants can be effectively done through the combination of vegetation indices and orthophotomosaic analyses since the finer scale of these products facilitates the identification and monitoring of natural gaps and tree canopies,

which are essential for understanding forest dynamics.

- 3) Although not being evaluated by from unmanned aerial vehicles, for areas of *Pinus* spp. and *Eucalyptus* spp., the tests performed on these coverages are relevant for future research that seeks to monitor of these specific species due to the homogeneity of these canopies.
- 4) The highest correlation coefficients for *Coffea* spp. was the Excess Green index and the Excess Red minus Green index was highest for Forest Remnant 1 and Forest Remnant 2. The performance of these visible spectrum indices has confirmed the potential of low-cost tools in meeting agricultural and environmental needs, which can lead to appropriate ecological management and conservation practices as well as strengthen national coffee productivity.
- 5) Finally, it was confirmed that UAV imagery has the potential to validate satellite-derived data and that low-cost platforms can strengthen large-scale monitoring.

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SUPPLEMENTARY MATERIAL

Appendix S1: (Tables SI, SII and Figure S1).

