

1   **Remotely-sensed vegetation greening along a restoration gradient of a tropical forest, Kibale**  
2   **National Park, Uganda**

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15   **A short informative containing the major key words:** This work assesses 20 years of remotely-  
16   sensed vegetation index data across a tropical forest restoration project area in Kibale National  
17   Park, Uganda, and evaluates the utility of vegetation indices to monitor the rate of forest  
18   regeneration.

19

20   **Running title:** Vegetation greening along a restoration gradient

21

## 22    **Abstract**

23    Restoration has now emerged as a global priority, with international initiatives such as the “UN  
24    Decade on Ecosystem Restoration (2021-2030)”. To fulfil the large-scale global restoration  
25    ambitions, an essential step is the monitoring of vegetation recovery after restoration interventions.  
26    The aim of this study was to evaluate the utility of remotely-sensed vegetation indices, Normalized  
27    Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), to monitor the rate of  
28    forest regeneration across a tropical forest restoration project area in Kibale National Park, Uganda.  
29    As a result, we observed non-linear patterns in NDVI and EVI across the first 25 years of recovery.  
30    Both NDVI and EVI increase for the first 10 years of forest regeneration. This “greening” phase  
31    could be used as the indicator of successful onset of forest recovery. In particular, the decline of  
32    elephant grass, which suppresses the natural regeneration of trees in our area, can be detected as an  
33    increase in NDVI. Primary forests differed from the 25-year-old regenerating forests based on the  
34    unique combination of low mean and low seasonal variation in EVI. Our results, therefore, suggest  
35    that the long-term success of forest restoration could be monitored by evaluating how closely the  
36    combination of mean, and degree of seasonal variation in EVI, resembles that observed in the  
37    primary forest.

38  
39    **Keywords:** Africa - EVI - NDVI - restoration - tropical forest - vegetation index

## 41    **Introduction**

42    Restoration of forests has now emerged as a global priority, with international initiatives such as the  
43    “UN Decade on Ecosystem Restoration (2021-2030)” (UN, 2021) and “The Bonn Challenge”  
44    (IUCN, 2020). The rapid loss of tropical forests (Hansen et al., 2013; FAO, 2015) has profound

45 consequences on biodiversity and ecosystem functioning (Chapin et al., 2000; Millennium  
46 Ecosystem Assessment, 2005). The area of tropical secondary forests has been increasing (Hansen  
47 et al., 2013) but natural regeneration is not always sufficient to ensure forest recovery (Paul,  
48 Randle, Chapman, & Chapman, 2004). Natural regeneration can fail especially if large forest areas  
49 have already been lost, seed-sources are far away, or environmental conditions are too poor for  
50 regeneration (Arroyo-Rodríguez et al., 2017). For example, fast-colonizing pioneer vegetation,  
51 together with fire, can arrest forest regeneration (Duclos, Boudreau, & Chapman, 2013; Wheeler et  
52 al., 2016). In such cases, active restoration measures (e.g., planting seedlings or spreading seeds), or  
53 passive restoration measures that remove human disturbances (e.g., excluding grazing or protection  
54 from fire) are needed to enable forest recovery (Lamb, Erskine, & Parrotta, 2005; Shono,  
55 Cadaweng, & Durst, 2007).

56 To fulfil the large-scale global restoration ambitions, an essential step is the monitoring of  
57 vegetation recovery after restoration interventions (Ruiz-Jaen & Aide, 2005). Typically, restoration  
58 success is monitored with field-measured attributes, e.g., vegetation cover, tree density or biomass,  
59 but frequent field assessments can be challenging with limited monitoring budgets (Ruiz-Jaen &  
60 Aide, 2005; Viani et al., 2017). The development of remote monitoring technologies could enable  
61 cost-effective assessment of vegetation recovery (Reif & Theel, 2017). For example, unmanned  
62 aerial vehicles can be used in monitoring the tropical forest recovery (Zahawi et al., 2015; Reis et  
63 al., 2019). Another potential source of data are satellite-based vegetation indices, Normalized  
64 Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), which have been  
65 commonly used to measure vegetation activity at the land surface (Huete, Didan, van Leeuwen,  
66 Miura, & Glenn, 2011; Didan & Munoz, 2019).

67 Vegetation indices measure the “greenness” of the canopy, i.e., a combination of leaf  
68 chlorophyll content, leaf area, canopy cover and canopy structure (Glenn, Huete, Nagler, & Nelson,  
69 2008; Didan & Munoz, 2019). These indices are based on the biological phenomenon that

70 chlorophyll a and b in plant leaves absorb red wavelengths, while plant leaves scatter near-infrared  
71 (NIR) wavelengths (Tucker, 1979). In the tropics, vegetation indices have been previously used for  
72 land-cover classification and to detect land-cover dynamics (Tucker, Townshend, & Goff 1985;  
73 Hartter, Ryan, Southworth, & Chapman, 2011; Setiawan, Yoshino, & Prasetyo, 2014; Vijith &  
74 Dodge-Wan, 2020; Wanyama, Moore, & Dahlin, 2020), map forest disturbances (Murillo-Sandoval,  
75 Van Den Hoek, & Hilker, 2017), predict forest resilience to drought (Verbesselt et al., 2016),  
76 monitor natural succession (Caughlin et al., 2021), estimate large-scale patterns in biomass (Anaya,  
77 Chuvieco, & Palacios-Orueta, 2009) or primary production (Sjöström et al., 2011), and detect  
78 seasonal phenological rhythms and photosynthetic capacity (Xiao, Hagen, Zhang, Keller, & Moore,  
79 2006; Brando et al., 2010; Valtonen et al., 2013). For example, in the Amazon, the first phase of  
80 forest regrowth can be detected as an increase in NDVI (Steininger, 1996). Outside tropics,  
81 vegetation indices have been used to monitor vegetation change across restoration and afforestation  
82 areas (Verbesselt, Hyndman, Newnham, & Culvenor, 2010; Sun et al., 2015; Zhang et al., 2016;  
83 Wu, Yu, Zhang, Du, & Zhang, 2019; Wang et al., 2020). However, to our knowledge, studies  
84 exploring the utility of remotely-sensed vegetation indices for monitoring the tropical forest  
85 recovery following restoration activities are yet lacking.

86 In this work, we assessed 20 years of vegetation index data across a tropical forest restoration  
87 project area in Kibale National Park, Uganda, together with field-based vegetation monitoring  
88 dataset. Our goal was to evaluate the utility of remotely-sensed vegetation indices to monitor the  
89 rate of forest regeneration in Afrotropics, where studies evaluating the restoration success have been  
90 generally scarce (Ruiz-Jaen & Aide, 2005). The restoration project was established in 1994 in an  
91 area where elephant grass (*Cenchrus purpureus* (Schumach.) Morrone), also known as napiergrass,  
92 and fires, suppressed the natural regeneration of tree seedlings and thereby prevented forest  
93 recovery (UWA-FACE, 2015). In this area, active restoration (i.e., planting with native trees and  
94 prevention of natural growth from fire), and passive restoration (i.e., prevention from fire), has

95 taken place since 1995. Our specific study questions were: 1) Does the vegetation greenness of  
96 restored forests converge to level observed in the nearby primary forest (the target state of  
97 restoration), as the restored forests age? 2) How does the vegetation greenness in the restored  
98 forests, and in the primary forest, vary seasonally? 3) How do the remotely-sensed vegetation index  
99 values relate to ground-measured stand basal area, shrub cover or elephant grass cover?

100 We hypothesize that the onset of forest regeneration after restoration interventions can be  
101 detected as increased vegetation greenness, as a product of an increase in tree density, leaf area and  
102 canopy cover (Foody & Curran, 1994; Wheeler et al., 2016). However, as the restored forests age,  
103 vegetation greenness should converge to levels observed in the nearby primary forest (Steininger,  
104 1996). Alternatively, vegetation greenness could reach its maximum in intermediate-aged  
105 regenerating forests. This is possible because as the canopy cover reaches 100%, vegetation indices  
106 measure the greenness of the plant leaves forming the canopy (Glenn et al., 2008). In this case,  
107 intermediate-aged regenerating forests, with a fast turnover of leaves in the canopy, could appear  
108 greener than the primary forest canopy, with older tree leaves hosting epiphyll growth, necroses and  
109 damage (Roberts, Nelson, Adams, & Palmer, 1998).

110

## 111 **2. Materials and Methods**

### 112 2.1 Study area

113 This study was conducted in Kibale National Park (Figure 1), located within the Albertine Rift,  
114 Western Uganda (Struhsaker, 1997; Plumptre et al., 2003; Hartter et al., 2011). Kibale National  
115 Park (795 km<sup>2</sup>, 900–1590 m a.s.l.) represents medium-altitude tropical moist forest but includes also  
116 reforestation areas, areas that have transitioned from forest to agriculture, grasslands and wetlands  
117 (Laporte, Walker, Stabach, & Landsberg, 2008; Hartter et al., 2011). The mean monthly  
118 temperature ranges between 20.8 and 22.1°C (Figure S1, Supplementary Material), and the study

119 area has two distinct rainy seasons from March to May and from August to November (Figure S2,  
120 Supplementary Material), with a long-term mean annual precipitation of 1,475 mm (Struhsaker,  
121 1997).

122 Kibale National Park hosts over 500 plant species, of which 330 are trees (Plumptre et al.,  
123 2003). In the mature forest, trees reach over 30 m height, the forest has a closed overstory canopy,  
124 with little or no herbaceous vegetation in the understory, or light reaching the understory (Wing &  
125 Buss, 1970). Seven successional vegetation types have been described in Kibale (Wing & Buss,  
126 1970), with early stages largely dominated by elephant grass and *Hyparrhenia* spp. grasses and  
127 *Acanthus pubescens* Engl. shrubs. Arrested succession is common in Kibale, where the  
128 aforementioned grasses and shrubs, together with invasive shrub *Lantana camara* L. and fire, can  
129 prevent forest regeneration (Paul et al., 2004; Lawes & Chapman, 2006; Duclos et al., 2013;  
130 Wheeler et al., 2016).

131

132 2.2 Restoration project area

133 Kibale National park has an approximately 10,000 ha restoration project area run by the Uganda  
134 Wildlife Authority (UWA) and Forests Absorbing Carbon dioxide Emission (FACE) the future  
135 foundation (Omeja et al., 2011; UWA-FACE, 2015; Wheeler et al., 2016) (Figure 1; Figure S3,  
136 Supplementary Material). In this part of the park, elevation ranges between 1,000 and 1,440 m a.s.l.  
137 (IRI/LDEO Climate Data Library, 2020). The project was established to an area where moist semi-  
138 deciduous forests were largely cut down by agricultural encroachers in the 1970s and 1980s  
139 (Chapman & Lambert, 2000; UWA-FACE, 2015). After agriculture was banned in the area and  
140 settlers relocated, the area was largely colonized by elephant grass, and together with fire, it  
141 suppressed naturally regenerating tree seedlings and thereby prevented forest recovery (UWA-  
142 FACE, 2015; Wheeler et al., 2016). Active restoration planting, along with protection from fire, has

143 taken place annually since 1995 (UWA-FACE, 2015) (the exceptions being years 2001 and 2013-  
 144 2015, when no planting took place; see details in Figures S3-S4, Supplementary Material). The  
 145 native trees planted (400 ha<sup>-1</sup>) included *Bridelia micrantha* (Hochst.) Baill, *Cordia africana* Lam,  
 146 *Cordia ugandensis* S.Moore, *Croton macrostachys* Hochst. ex A.Rich., *Croton megalocarpus*  
 147 Hutch, *Ficus natalensis* Hochst, *Mimusops bagshawei* S.Moore, *Prunus africana* (Hook.f.)  
 148 Kalkman, *Spathodea campanulata* P.Beauv., and *Warburgia ugandensis* Sprague (Omeja et al.,  
 149 2011; UWA-FACE, 2015; Wheeler et al., 2016). Field assessments in 2005 and 2013 have shown  
 150 that the restoration planting has been generally successful, with increasing trends in tree stem  
 151 density and above ground biomass (Wheeler et al., 2016).

152 The restoration project area also includes large areas representing passive restoration, i.e.,  
 153 protection of natural regrowth from fire (Figure 1). These are areas where the forest was cleared in  
 154 the past, but a large number of remnant trees was present when the restoration project started (W.  
 155 van Goor, personal communication, October 12, 2020). To the east, the restoration project area is  
 156 bordered by a belt of primary forest (Figure 1), herein referred to as the reference area, i.e., the  
 157 target state of the restoration.

158

159 2.3 Vegetation indices

160 The two most commonly used vegetation indices, NDVI and EVI, were included in this work. The  
 161 values of NDVI range between -1 and +1 so that areas with higher canopy greenness receive the  
 162 highest positive values (Glenn et al., 2008; Didan & Munoz, 2019). The values of NDVI are  
 163 calculated as follow:

164 
$$NDVI = \frac{NIR - \textcolor{red}{i}}{NIR + \textcolor{red}{i}}$$

165 where *NIR* and *Red* indicate the reflectance values of NIR and red light, respectively. Across Africa,  
 166 NDVI is low in areas with sparse vegetation cover (e.g., Sahara and Sahelian zone) and reaches the  
 167 highest values in dense humid forests (Tucker et al., 1985; Goetz & Prince, 1999). However, NDVI  
 168 tends to saturate when vegetation density is very high (Huete et al., 2002). EVI was developed to  
 169 perform better in high biomass regions, for improved de-coupling of canopy-background signal, as  
 170 well as to reduce atmospheric influences (Huete et al., 2002; Didan & Munoz, 2019). The values of  
 171 EVI are calculated as follow (Didan & Munoz, 2019):

$$172 \quad EVI = 2.5 \times \frac{NIR - \textcolor{red}{i}}{NIR + 6 \times \textcolor{red}{i}} - 7.5 \times \textcolor{red}{i} + 1 \textcolor{red}{i}$$

173 where *Blue* indicates the reflectance value of blue light. We included both NDVI and EVI because  
 174 they could complement each other. NDVI has a higher dynamic range in low greenness values, and  
 175 therefore better ability to separate semiarid habitat types from each other, while EVI has a higher  
 176 dynamic range in high greenness values, and is better in separating humid forested habitat types  
 177 from each other (Huete et al., 2002).

178 We used the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation  
 179 Indices (MOD13Q1) Version 6 dataset (Didan & Munoz, 2019; USGS, 2020). This data represents  
 180 16-day NDVI and EVI composites at  $250 \times 250$  m spatial resolution. The composites are generated  
 181 with an algorithm that chooses the best available pixel value from the 16-day period. The NDVI and  
 182 EVI datasets were downloaded from IRI/LDEO Climate Data Library (2021a), and the vegetation  
 183 index quality data from IRI/LDEO Climate Data Library (2021b). We determined the validity of  
 184 vegetation index values following the four criteria used in Samanta et al. (2010) and Samanta,  
 185 Ganguly, Vermote, Nemani, and Myneni (2012a). The vegetation index value was considered valid  
 186 and selected for further analyses, if: 1) “VI Quality” was “good quality” or “check other quality  
 187 assessment (QA)”. 2) “VI Usefulness”, which has 16 levels (Didan & Munoz, 2019) ranged

188 between 0 and 11. 3) Clouds were absent, i.e., no “adjacent cloud detected”, no “mixed clouds”, and  
189 no “possible shadow”. 4) “Aerosol quantity” was either “low” or “intermediate”.

190 The NDVI and EVI datasets were downloaded across a rectangular area 30.26 – 30.41°E, and  
191 0.25 – 0.50°N covering a total of 7,866 grids (at 250 × 250 m spatial resolution), including both the  
192 restoration area and nearby primary forests. For each grid, the NDVI and EVI values were  
193 downloaded between 30 April 2000 and 25 December 2020. This time span covers a total of 476  
194 potential time-points (the 16-day composites), and each fully covered year has 23 time-points.  
195 These search criteria produced a total of 3,724,858 vegetation index values for each NDVI and EVI.  
196 Based on vegetation index quality data, 2,790,260 (75%) of these values were considered valid and  
197 were selected for further analyses.

198

199 2.4 Grid selection and management classes

200 Out of the 7,866 grids, a total of 2,853 grids were selected for further analyses (Figure 1; Figure S4,  
201 Supplementary Material). The grid was selected if its center was located either inside the planted  
202 areas or inside areas designated for passive restoration, or if it represents primary forest. Primary  
203 forest grids include the primary forest belt on the east side of the restoration project area (Figure 1),  
204 but they excluded grids classified as “degraded forest” in earlier land-classifications (UWA-FACE,  
205 2015).

206 We further classified the 2,853 grids to seven management classes: 1) Primary forest (1,719  
207 grids), 2) Passive restoration (430 grids), 3) Planted 1995–1999 (396 grids), 4) Planted 2000–2004  
208 (76 grids), 5) Planted 2005–2009 (106 grids), 6) Planted 2010–2011 (81 grids), and 7) Planted  
209 2016–2020 (45 grids). This classification aimed to divide the planting years into 5-year intervals.  
210 However, since no planting took place between 2013 and 2015, and the 2012 planted area was so

211 small that it contained no grids (Figure S4, Supplementary Material), one management class  
212 (Planted 2010–2011) includes only two planting years.

213

214 2.5 Vegetation measurements

215 To study how NDVI and EVI are related to the field-measured characteristics of the vegetation, we  
216 extracted data across 174 vegetation monitoring study sites (Figure S3, Supplementary Material),  
217 censused in 2013 (Owiny et al., unpublished). At each study site, large trees (> 20 cm diameter at  
218 breast height; DBH) were censused in a 40 m × 20 m plot. Small trees and poles (10–20 cm DBH)  
219 were censused in a 20 m × 20 m plot, saplings (5–10 cm DBH) in a 20 m × 10 m plot, and seedlings  
220 (< 5 cm DBH) in a 10 m × 10 m plot; all plots being nested and sharing one corner. For each study  
221 site, we estimated the stand basal area (m<sup>2</sup> ha<sup>-1</sup>) based on trees with DBH ≥ 5 cm. The basal area has  
222 been frequently used as a surrogate of forest biomass (Brown, Gillespie, & Lugo, 1989). We also  
223 used the visually estimated shrub and elephant grass covers for each 40 × 20 m plot. The cover  
224 values were estimated on a scale: 0 (0%), 0.5 (<10%), 1 (10%), 2 (20%), 3 (30%),..., 10 (100%).

225

226 2.6 Statistical analyses

227 We first used chronosequence approach to find out if the vegetation greenness of the restored  
228 forests converges through time to levels observed in the nearby primary forest. The mean NDVI and  
229 EVI in 2020 was calculated for each grid representing active or passive restoration (1,134 grids).  
230 The year 2020 was selected to maximize the length of the chronosequence. For each grid, we  
231 calculated the forest age (years since restoration started). Grids representing passive restoration  
232 were assigned forest age 25 years. For each forest age, mean vegetation greenness (across grids)  
233 was plotted along the chronosequence.

234 To model the pattern in vegetation greenness along the chronosequence, three competing  
235 models were fitted, with NDVI or EVI as response and forest age as a predictor variable: 1) linear  
236 model, 2) three-parameter asymptotic exponential model, which allows the greenness to slowly  
237 approach an asymptote, fitted with self-starting non-linear function “SSasymp” in R (R Core Team,  
238 2021), and 3) quadratic model allowing greenness to first increase and then decrease. The fit of the  
239 three competing models was compared with the second-order Akaike Information Criterion (AICc;  
240 Burnham & Anderson, 2002) calculated with package “MuMIn” in R (R Core Team, 2021).

241 For each of the seven management classes, we calculated mean annual and mean monthly  
242 NDVI and EVI. These were calculated from the full time-series with 476 time-points (the 16-day  
243 composites) representing mean NDVI and EVI values for each of the seven management classes  
244 (mean across the grids). These time-series included some missing values (4–14%), due to missing  
245 time-points in the original MODIS datasets, and due to omission of poor-quality data (based on the  
246 vegetation index quality data, see above). The missing values in the seven time-series were replaced  
247 with linear interpolation using package “imputeTS” in R (R Core Team, 2021).

248 To illustrate the 20-year time-trends in the vegetation greenness of each management class,  
249 the mean annual NDVI and EVI was plotted between 2001-2020 (excluding 2000 which was not  
250 fully covered). Time trends were modelled with Generalized Additive Models (GAMs), using  
251 package “mgcv” in R (R Core Team, 2021), and following Zuur, Ieno, Walker, Saveliev, and Smith  
252 (2009, p. 43), with cross-validation used to estimate the optimal amount of smoothing for the  
253 smoothing term (the explanatory variable) and with cubic regression splines.

254 To describe the seasonal patterns in vegetation greenness, the mean monthly NDVI and EVI  
255 of each management class, was first plotted together with mean monthly precipitation (see sources  
256 in Figure S2, Supplementary Material). We also illustrated how the degree of seasonal variation in  
257 NDVI or EVI relates to their mean values (Requena-Mullor, Reyes, Escribano, & Cabello, 2018)

258 across the seven management classes. As a measure of degree of seasonal variation, we used  
259 coefficient of variation (CV) calculated from the mean monthly values.

260 Finally, we described how NDVI and EVI are related to the three field-measured structural  
261 characteristics of the vegetation (stand basal area, shrub cover, elephant grass cover). The 174  
262 vegetation study sites were located in 146 grids ( $250 \times 250$  m) from which data of NDVI and EVI  
263 was available. For each of these 146 grids, we calculated the mean value for each of the three  
264 vegetation structure variables, and the mean of NDVI and EVI in 2013, i.e., the year of the  
265 vegetation census. To describe associations between NDVI or EVI and the three vegetation  
266 structure variables, GAMs were fitted following the same method as detailed above. All statistical  
267 analyses were run with R version 4.0.3 (R Core Team, 2021).

268

269 **3. Results**

270 3.1 Do NDVI and EVI converge through time to level of primary forest?

271 The patterns of both NDVI and EVI along the chronosequence were best described with the  
272 quadratic models (Figure 2; Table S1, Supplementary Material). Both NDVI and EVI increased for  
273 the first 10 years of forest regeneration but after 20 years, both start to decline towards lower levels  
274 observed in the primary forest. The pattern of vegetation greening after restoration planting is also  
275 visible in the annual time-series of NDVI and EVI (Figures S5-S6, Supplementary Material).

276

277 3.2 Seasonal pattern in NDVI and EVI

278 Both NDVI and EVI follow clear seasonal patterns; the two annual greenness peaks follow  
279 precipitation peaks with approximately one-month time-lag (Figure 3). The seasonal variation is  
280 generally larger, and greenness peaks narrower, in the management class Planted 2016-2020, which

represents mostly elephant grass during our study period. The seasonal variation in greenness (measured as CV) generally decreases as the mean level of greenness increases (Figure 4). The primary forest can be distinguished from regenerating forests by the unique combination of low seasonal variation and low mean level in EVI. On the contrary, a combination of CV and mean level in NDVI cannot be used to distinguish the primary forest from regenerating forests.

### 3.3 How vegetation indices relate to ground-measured vegetation structure?

NDVI peaks when stand basal area reaches approx.  $10 \text{ m}^2 \text{ ha}^{-1}$ , and declines in values higher than this (GAM; estimated degrees of freedom (edf) = 4.7,  $F = 15.6$ ,  $p < 0.001$ ; Figure 5A). Also, EVI peaks when stand basal area reaches approx.  $10 \text{ m}^2 \text{ ha}^{-1}$ , but declines steeply in values higher than this (GAM; edf = 5.0,  $F = 19.8$ ,  $p < 0.001$ ; Figure 5B).

Furthermore, both NDVI (edf = 1.0,  $F = 6.25$ ,  $p = 0.014$ ; Figure 5C), and EVI increase as shrub cover increases (edf = 2.5,  $F = 24.4$ ,  $p < 0.001$ ; Figure 5D). On contrary, NDVI decreases steeply as the elephant grass cover increases (edf = 2.8,  $F = 45.0$ ,  $p < 0.001$ ; Figure 5E) while association between EVI and elephant grass cover is non-significant (edf = 2.1,  $F = 1.6$ ,  $p = 0.199$ ; Figure 5F).

## **4. Discussion**

Our results show that the onset of tropical forest regeneration, after restoration interventions, can be detected as an increase in vegetation greenness. This “greening” phase, detected both in the chronosequence (Figure 2), and in the annual time-series (Figures S5-S6, Supplementary Material), takes place when the tree basal area increases up to  $10 \text{ m}^2 \text{ ha}^{-1}$  (Figure 5). The common shrub species, *Acanthus pubescens* and *Lantana camara*, are likely to contribute significantly to the

304 observed greening pattern (Figure 5; Wheeler et al., 2016). Notably, the decline of the elephant  
305 grass, i.e., the species which suppresses the natural regeneration of trees in our study area (Wheeler  
306 et al., 2016), is detectable as an increase in NDVI (Figure 5). The duration of this greening phase is  
307 likely to differ significantly among geographical regions, and depends on environmental conditions,  
308 and severity of disturbance. For example, in the Amazon, NDVI increased to levels similar to the  
309 primary forest in only a few years of regeneration (Steininger, 1996).

310       Vegetation greenness reached its maximum in intermediate-aged regenerating forests (Figure  
311 2), indicating that neither NDVI nor EVI can be used as simple measures of long-term forest  
312 recovery. In our study area, the intermediate-aged regenerating forests are characterized by dense  
313 thickets of shrubs, mainly composed of *Acanthus pubescens* and other large-leaved shrubs and  
314 herbs, such as *Triumfetta* sp., *Aframomum* sp., *Lantana camara* and *Marantochloa leucantha*  
315 (K.Schum.) Milne-Redh. (pers. obs.). When the canopy cover reaches 100%, vegetation indices  
316 measure the greenness of the plant species forming the canopy, and plant species can differ  
317 markedly in their canopy greenness (Glenn et al., 2008). The canopy of the intermediate-aged  
318 forests can appear greener than the canopy of primary forest if the canopy is dominated by plant  
319 species which have particularly high chlorophyll content or canopy architecture producing high  
320 greenness (Glenn et al., 2008), or if there is a faster turnover in canopy leaves. Early successional  
321 fast-growing trees, shrubs and forbs tend to have lower leaf longevity than slower-growing late-  
322 successional trees (King, 1994; Kikuzawa & Ackerly, 1999; Ishida et al., 2008). As the tree leaves  
323 age, they accumulate epiphyll growth, necroses and damages, which are detectable as changes in  
324 NIR (Roberts et al., 1998). Moreover, EVI is more sensitive to changes in NIR than NDVI (Huete,  
325 et al., 2011). This could explain why after 20 years of recovery, EVI (and less so NDVI) started to  
326 decline towards levels observed in the primary forest. Presumably, in this “browning” phase, late-  
327 successional tree canopies increasingly cover shrubs of the understory. Further studies are needed to

328 find out if, and when, the greenness of the restored forests finally converge to the primary forest  
329 level.

330 Our results largely comply with previous observations across the tropics. Higher levels of  
331 NDVI in regenerating forests, compared to primary forests, was previously reported in Kibale NP  
332 by Hartter et al. (2011). In the Amazon, regenerating tropical forests, between 5 to 20 years old,  
333 showed NDVI comparable, or slightly higher, than the primary forest (Steininger, 1996). In Borneo,  
334 the rapid regrowth of secondary vegetation after logging (classified as woody savannas and  
335 grasslands) showed slightly higher EVI than the evergreen broad-leaved forests, i.e., vegetation  
336 prior to logging, but overall, these vegetation types were not distinguishable based on EVI (Vijith &  
337 Dodge-Wan, 2020). The levels of NDVI and EVI in our data comply with previous observations  
338 from a seasonal tropical humid broad-leaved forest in Tapajos, Brazil (Huete et al., 2002) and  
339 tropical broad-leaved forest in Borneo (Vijith & Dodge-Wan, 2020); both of these works were  
340 based on MODIS datasets as used in this work. However, the level of NDVI in our data was higher  
341 than what was previously reported in Kibale NP by Hartter et al. (2011) but slightly lower than  
342 reported in the Amazon (Steininger, 1996); both works based on Landsat images. As noted by  
343 Huete et al. (2002), vegetation index values produced by different sensors can deviate especially  
344 across high greenness values.

345 The biomass of tropical forests cannot be simply predicted based on satellite-derived NDVI or  
346 EVI, because the associations are strongly non-linear (Figure 5). Also, several previous works have  
347 failed to establish correlations between tropical forest biomass and NDVI (Foody et al., 2001;  
348 Foody, Boyd, & Cutler, 2003; Freitas, Mello, & Cruz, 2005) or EVI (Anaya et al., 2009). We  
349 assume that the peak of greenness at stand basal area  $10 \text{ m}^2 \text{ ha}^{-1}$  is explained by the dense shrub  
350 cover in this regeneration phase. Our results imply that “browning” trends (de Jong, Verbesselt,  
351 Zeileis, & Schaepman, 2013; Higginbottom & Symeonakis, 2020), are not necessarily only a sign of  
352 human disturbance (Murillo-Sandoval et al., 2017), or drought (Anyamba & Tucker, 2005), but in

353 some cases could also be a sign of increasing forest biomass and ecosystem recovery. Furthermore,  
354 all "greening" trends may not be indicative of an increase in biomass. For example, in Senegal, the  
355 transition from woody vegetation to the dominance of shrubs was detected as increased NDVI  
356 (Herrmann & Tappan, 2013).

357       The long-term success of forest restoration could be monitored by evaluating how closely the  
358 combination of mean, and degree of seasonal variation in EVI, resembles that observed in the  
359 primary forest, i.e., the target state of restoration. NDVI is not suitable for this purpose, presumably  
360 because it saturates as the vegetation density becomes very high (Huete et al., 2002; Didan &  
361 Munoz, 2019). Previously, the combination of mean and seasonal variation of vegetation greenness  
362 has been used to classify vegetation types on landscape or continental level (Paruelo, Jobbagy, &  
363 Sala, 2001; Alcaraz-Segura, Paruelo, Epstein, & Cabello, 2013; Requena-Mullor et al., 2018). As  
364 shown by our study (Figure 3), and previous studies (e.g., Brando et al., 2010), NDVI and EVI are  
365 highly useful for understanding the seasonal patterns in tropical rain forests. The bi-annual seasonal  
366 pattern in vegetation greenness can be mechanistically explained by the leaf flush during and after  
367 the rainy season (Brando et al., 2010; Samanta et al., 2012b). During dry-season, vegetation  
368 greenness decreases as leaves age, accumulate epiphyll growth, leaf necrosis and damage (Roberts  
369 et al., 1998; Samanta et al., 2012b). The generally smaller seasonal variation in greenness towards  
370 older forests is likely explained by the ability of trees to buffer drought with their deep roots  
371 (Anderson et al., 2015).

372       To conclude, remotely-sensed vegetation indices can provide valuable information to monitor  
373 forest recovery after restoration interventions. NDVI and EVI datasets can be used as cost-effective  
374 tools in monitoring of vegetation recovery across large-scale restoration or afforestation areas.  
375 Grids where the "greening" phase is not detected could be inspected in the field, enabling corrective  
376 actions to take place. For monitoring the transition from grassland to tropical forest, NDVI and EVI  
377 complement each other. NDVI is more sensitive detecting the withdrawal of the grasses, while EVI

378 is more sensitive for detecting the different successional stages between intermediate-aged  
379 regenerating and primary forest. Previous works in the restoration area of Kibale NP, Uganda, have  
380 reported the successful establishment of the planted trees, natural regeneration of several tree  
381 species (Omeja et al., 2011), and recovery-patterns in tree communities (Wheeler et al., 2016), fruit-  
382 feeding butterfly communities (Nyafwono, Valtonen, Nyeko, & Roininen, 2014) and bird  
383 communities (Latja, Valtonen, Malinga, & Roininen, 2016). In the future, remote sensing could be  
384 also utilized to predict recovery of diversity patterns (Khare, Latifi, & Rossi, 2019; Laliberte,  
385 Schweiger, & Legendre, 2020) or to monitor invasive species (Royimani, Mutanga, Odindi, Dube,  
386 & Matongera, 2019), such as the invasive shrub *Lantana camara*, across large-scale restoration  
387 areas.

388

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393

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## 634 **Supplementary Material**

635 This manuscript contains Supplementary Material file entitled  
636 “valtonen\_etal\_SupplementaryMaterial.docx”

## 638 **Figure legends**

639 Figure 1. Map of the study area in Kibale National Park, Uganda. Symbols show the 2,853 grids  
640 selected for analyses (a more detailed map showing areas with planting years in Figure S3,  
641 Supplementary Material). Map generated with QGIS version 3.14.

643 Figure 2. Mean ( $\pm$ SE) (A.) NDVI and (B.) EVI in 2020, for each forest age, i.e., years since  
644 restoration started (the quadratic models are shown on top). Grids representing passive restoration  
645 were given forest age 25 years. The mean of the primary forest is shown as a dotted horizontal line.

646

647 Figure 3. Mean monthly (A.) NDVI and (B.) EVI in the seven management classes. The vertical  
648 bars show mean monthly precipitation (sources in Figure S2, Supplementary Material).

649

650 Figure 4. Combination of seasonal variation (coefficient of variation; CV) and the mean level in  
651 greenness for (A.) NDVI and (B.) EVI in the seven management classes.

652

653 Figure 5. Mean NDVI and EVI in 2013, and ground-measured (A-B.) stand basal area of trees DBH  
654  $\geq 5$  cm, (C-D.) shrub cover, and (E-F.) elephant grass cover across the 146 grids. If statistically  
655 significant, estimated smoothing curves (cubic regression splines) and point-wise 95% confidence  
656 bands from Generalized Additive Models are shown on top.