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Complete List of Authors:	Shimizu, Katsuto; Kyushu University, Graduate School of Bioresource and Bioenvironmental Sciences Ponce-Hernandez, Raul; Trent University Ahmed, Oumer S.; Trent Univ Ota, Tetsuji; Kyushu University, Institute of Decision Science for a Sustainable Society Win, Zar Chi; Kyushu university, Graduate School of Bioresource and Bioenvironmental Sciences Mizoue, Nobuya; Kyushu University, Faculty of Agriculture Yoshida, Shigejiro; Kyushu university, Faculty of Agriculture
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Using Landsat time series imagery to detect forest disturbance in selectively logged tropical forests in Myanmar

Katsuto Shimizu^a, Raul Ponce-Hernandez^b, Oumer S. Ahmed^b, Tetsuji Ota^{c*}, Zar Chi Win^a, Nobuya Mizoue^d, Shigejiro Yoshida^d

^a Graduate School of Bioresource and Bioenvironmental Sciences, Kyushu University, 6-10-1 Hakozaki, Higashi-ku, Fukuoka 812-8581, Japan
^b Applied Geomatics, Remote Sensing and Land Resources Laboratory, School of the Environment, Trent University, Ontario K9J 7B8, Canada
^c Institute of Decision Science for a Sustainable Society, Kyushu University, Fukuoka 812-8581, Japan
^d Faculty of Agriculture, Kyushu University, Fukuoka 812-8581, Japan

Katsuto Shimizu (dulvrq.3317nau@gmail.com); Raul Ponce-Hernandez (rponce@trentu.ca); Oumer S. Ahmed (osahmed@trentu.ca); Tetsuji Ota (chochoji1983@gmail.com); Zar Chi Win (zarchiwin8@gmail.com); Nobuya Mizoue (mizoue@agr.kyushu-u.ac.jp); Shigejiro Yoshida (syoshida@agr.kyushu-u.ac.jp)

* Corresponding author. Tetsuji Ota, Institute of Decision Science for a Sustainable Society, Kyushu University, Fukuoka 812-8581, Japan. Tel.: +81-926-422-868; Fax: +81-926-422-867; Email: chochoji1983@gmail.com

25

26 **Abstract**

27 Detecting forest disturbances is an important task for formulating mitigation strategies
28 for deforestation and forest degradation in the tropics. Our study investigated the utility
29 of Landsat time series imagery combined with a trajectory-based analysis for detecting
30 forest disturbances resulting exclusively from selective logging in Myanmar. Selective
31 logging was the only forest disturbance and degradation indicator used in this study as a
32 causative force. The results showed that the overall accuracy for forest disturbance
33 detection, based on selective logging was 83.0% in the study area. The areas affected by
34 selective logging and other factors accounted for 4.7% and 5.4%, respectively, of the
35 study area from 2000 to 2014. The detected disturbance areas were underestimated
36 according to error assessments; however, a significant correlation between areas of
37 disturbance and numbers of harvested trees during the logging year was observed,
38 indicating the utility of a trajectory-based, annual Landsat imagery time series analysis
39 for selective logging detection in the tropics. A major constraint of this study was the
40 lack of available data for disturbances other than selective logging. Further studies
41 should focus on identifying other types of disturbances and their impacts on future
42 forest conditions.

43

44 Keywords: Landsat; selective logging; time series; tropics.

45

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46 **Introduction**

47 Forest disturbances have important effects on forest structure, the carbon
48 budget, and ecosystem processes (Frolking et al. 2009; van Lierop et al. 2015). Most
49 disturbances are an integral part of the forest ecosystem; however, some natural and
50 human-induced disturbances can have undesirable impacts on forest functions (Hansen
51 et al. 2001; McDowell et al. 2015), which lead to deforestation and forest degradation.
52 Information regarding the location, timing and magnitude of disturbance events must be
53 quantified to understand disturbance processes and formulate mitigation strategies.

54 Tropical forests have made large contributions to the global carbon cycle and
55 biodiversity. For example, it is estimated that carbon stock in tropical forests account for
56 55% of the carbon stock in the world's forests (Pan et al. 2011) and that about
57 two-thirds of biodiversity hotspots are distributed in tropical forests (Brooks et al 2002).
58 However, adequate disturbance information is still lacking especially in the tropics
59 (Harris et al. 2012; Morales-Hidalgo et al. 2015). In the context of increasing forest
60 monitoring capacities via remote sensing and ground surveys in the last decade, time
61 series of satellite data comprising temporally dense satellite images over vast areas can
62 provide a comprehensive understanding of historical forest disturbances (Romijn et al.
63 2012; Romijn et al. 2015). Frequent cloud cover and fast vegetation recovery in the
64 tropics limit the detection of disturbances, as well as the characterization of their direct
65 causes, using the satellite images (Hirschmugl et al. 2014; Thapa et al. 2015). However,
66 recent developments in data preprocessing, as well as methods for detecting forest

67 changes, have made it possible to track forest changes using numerous satellite data.
68 The available approaches range from trajectory-based analyses (Kennedy et al. 2007;
69 Huang et al. 2010; Kennedy et al. 2010; Verbesselt et al. 2010; Verbesselt et al. 2012;
70 Hermosilla et al. 2015) to classification-based analyses (Grinand et al. 2013; Griffiths et
71 al. 2014). A number of studies have focused on detecting forest disturbances (Dutrieux
72 et al. 2015; Grogan et al. 2015; DeVries et al. 2015b), regrowth (DeVries et al. 2015a),
73 deforestation, and forest degradation (Helmer et al. 2010; Matricardi et al. 2010; Souza
74 et al. 2013; Hirschmugl et al. 2014; Shimabukuro et al. 2014; Reiche et al. 2015), or
75 forest cover loss (Potapov et al. 2012; Hansen et al. 2013; Potapov et al. 2014) in the
76 tropics. Despite an increasing number of studies focusing on the detection of forest
77 changes, applications of time series analyses of satellite imagery in the tropics are still
78 limited, especially for trajectory-based analyses, which provide detailed information
79 about forest changes (Banskota et al. 2014). Also, previous studies showed that yearly
80 or more frequent information extracted from time series of satellite data using
81 trajectory-based analysis is useful for characterizing relatively large-scale disturbance,
82 which can lead to stand replacement such as harvesting, forest fires and insect outbreaks
83 (e.g. Kennedy et al. 2015). However, detecting small scale forest disturbances which do
84 not involve stand replacement but lead to canopy gap formation in the stand such as
85 those created by selective logging in the tropics, has not been fully explored.

86 Selective logging is a common practice for timber production in the tropics. In
87 the selective logging system, only trees that are larger than the minimum exploitable

size are felled. Thus, it is a major challenge to detect the spatial extent of logged forests just a year or so following disturbance using Landsat-type satellite data due to the spatial resolution (Pereira et al. 2002). Thus, to understand changes in forest structure, we need a technique to detect such small-scale disturbances caused by selective logging. Many researchers have attempted to detect selective logging disturbances using Landsat images of the tropics. Asner et al. (2002) used Landsat reflectance and texture data to map selective logging operations. They showed that a part of the logging operations (i.e. the log deck) was visible, but other operations, such as skid trails or tree falls, were not. To overcome problems associated with conventional processing techniques, several studies utilized Spectral Mixture Analysis (SMA), such as Carnegie Landsat Analysis System (Asner et al. 2005; Asner et al. 2006) or Normalized Difference Fraction Index (Souza et al. 2005) for multitemporal and time series Landsat images (Souza et al. 2013; Hirschmugl et al. 2014; Shimabukuro et al. 2014), to detect forest disturbances resulting from selective logging. These studies showed positive results in the Brazilian Amazon and central Africa. However, there is a limitation regarding the application of SMA for forest monitoring in Southeast Asia, especially in mountainous areas, since SMA needs to consider the variation of spectral reflectance caused by topographic conditions (Miettinen et al. 2014).

Furthermore, past studies based on SMA merely used logging year records and high spatial resolution images to validate the existence of forest disturbances derived from selective logging. The capability of Landsat images to provide actual areas of

109 small-scale disturbances affected by selective logging should be investigated if changes
110 in forests are to be mapped accurately. Although it is possible to use the actual number
111 of harvested trees, which would be related to logging intensity, during a logging year to
112 validate the accuracy of detecting selective logging disturbances, this was rarely
113 considered in past studies. To map forest disturbances resulting from selective logging
114 in mountainous areas of tropical forests, alternative approaches are needed other than
115 SMA, and the detection of disturbances should be validated using both logging year
116 records and actual number of harvested trees during the logging year.

117 Myanmar is one of the most forest covered countries in Southeast Asia. Yet, its
118 rate of recent deforestation is the highest in Southeast Asia, rendering it as the
119 sub-continent. The Global Forest Resources Assessment 2015 (FAO 2015) showed that
120 forest cover in Myanmar decreased from 51.5% to 42.9% in the past 15 years, and its
121 annual forest loss for last 5 years (i.e. 2010-2015) was the third largest in the world.
122 Thus, characterizing the driver of forest change in Myanmar is an urgent issue. While
123 several studies have examined the states of natural forests in Myanmar and the factors
124 affecting forest changes such as selective logging (Win et al. 2009; Mon et al. 2012;
125 Win et al. 2012), they used bi-temporal change detection, which was the direct
126 comparison of bi-temporal pair of images (Hansen and Loveland 2012). Because of the
127 fast vegetation recovery dynamics in the tropics, these studies may underestimate the
128 forest changes. The time series of annual satellite images may provide more accurate
129 assessments of forest changes, and they may identify the direct causes, such as impacts

130 of logging operations on forest structure. A number of factors make the forests of
131 Myanmar suitable for this study. First, the number of logged trees has been recorded on
132 an annual basis. Secondly, there have been but few human-induced large-scale
133 disturbances in such forests (Mon et al. 2012). Therefore, selectively logged forests in
134 Myanmar are suitable sites for investigating the utility of time series of Landsat images
135 for the detection of small-scale disturbances caused by selective logging.

136 The objectives of this study were (1) to evaluate the accuracy of forest
137 disturbance detection for each year using a trajectory-based Landsat time series analysis,
138 and (2) to identify the location and total areas of disturbance caused by selective logging
139 operations using actual annual logging records consisting of logging year and the
140 number of logged trees in selectively logged forests.

141

142 **Study area and Data**

143 **Study area**

144 The study area is a part of the Bago Mountains, which are located in the central basin of
145 Myanmar (Figure 1). We analyzed selectively logged forests that cover 139 000 ha of
146 the Yedashe, Taungoo, Oktwin and Pyu Townships in the Taungoo district. There are
147 three seasons in this region: these are categorized as “hot”, “rainy” and “dry”. The hot
148 season lasts from March through May, while the rainy season starts in May and ends in
149 October, and the dry season is from October to March. Annual rainfall is about 2 000
150 mm in Taungoo Township. Elevation in the study area ranges from 109 to 579 m above

151 sea level, with an abrupt topography that has an average slope angle of about 10.5°. The
152 forests in this region are mixed deciduous forests, where *Tectona grandis*, *Xylia*
153 *xylocarpa*, and *Bambusa polymorpha* are the dominant species (Thein et al. 2007; Khai
154 et al. 2016).

155 The Myanmar Government has implemented selective logging operations
156 known as the Myanmar Selection System, to manage forests in this region since 1856.
157 The logging is operated in compartments, which are basic units that yield approximately
158 equal volumes of timber products on a 30-year felling cycle (Mon et al. 2012). The
159 logging operation for each compartment usually starts in May and lasts until February.
160 Skidding logged trees in such operations is conducted using elephants to minimize
161 damage to the soil and residual stands (Brunner et al. 1998).

162

163 **Remote sensing data**

164 Landsat time series images were obtained from the United States Geological
165 Survey Landsat (USGS) archives (<http://earthexplorer.usgs.gov/>). A total of 23 Landsat
166 Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operation Land
167 Imager (OLI) images were used (Table 1). The images were acquired between 2000 and
168 2014, for WRS2 path/row 133/47. According to our field observations in Bago
169 Mountains, the leaves of most deciduous trees are on until early February, and they start
170 to shed in late January. Thus, in this study, only images acquired from November to
171 early February were used to avoid the inclusion of leaf-off conditions. For each year of

the period, up to three Landsat images were selected to construct a Landsat time series, depending on the emergence of Scan Line Corrector (SLC)-off or clouds (and their shadows) in images.

175

176 **Field data**

To attribute disturbance factors area of forest in an image, selective logging record data were used to identify pixels at the locations where forest disturbances had occurred. The logging data for each compartment were obtained from the Forest Department of Myanmar. We extracted logging year and the number of harvested trees for each compartment from 2000 to 2013 in the study area. The study area consists of 392 compartments located in eight Reserved Forests (i.e. Kyaukmasin R.F., Lonyan R.F., Sabyin R.F., West Swa R.F., Kabaung R.F., Pyu Kun R.F., Pyu Chaung R.F., and Bondaung R.F.). The mean area of the compartments is 356 ha, and the areas ranged from 70 to 1 278 ha.

186

187 **Topographic data**

A Digital Elevation Model (DEM) was used to eliminate topographic effects in the Landsat time series. We used 30m resolution DEM from the Shuttle Radar Topographic Mission (SRTM), obtained from USGS archives (<http://earthexplorer.usgs.gov/>). The absolute horizontal and vertical accuracy are 8.8 m and 6.2 m, respectively, for 90 % of SRTM DEM in Eurasia (Rodriguez et al. 2006).

193 The original DEM was resampled and co-registered with the Landsat pixel allocation in
194 the study area.

195

196 **Methods**

197 The approaches and methods followed in this study are described in the
198 succeeding sections. The flowchart in Figure 2 summarizes the sequence of data
199 processing steps. First, each image in the Landsat time series was subjected to image
200 preprocessing, including atmospheric correction, normalization, topographic correction,
201 cloud masking, and gap filling. Then, forest change detection was implemented by the
202 LandTrendr algorithm (Kennedy et al. 2010) using calibrated parameters. Produced
203 disturbance maps indicating the locations and years of disturbances were aggregated to
204 their corresponding compartments. Selective logging information from 2000 to 2013
205 was also aggregated to each compartment. Then, the disturbance factors were attributed
206 to either selective logging or other factors. A visual interpretation was conducted for
207 randomly selected samples in order to validate the accuracy of the disturbance map
208 produced by LandTrendr. Additionally, to ensure that the LandTrendr algorithm could
209 detect disturbances resulting from selective logging, we investigated the disturbance
210 area ratio for compartments during the logged year, as well as the relationship between
211 the disturbance area and the number of harvested trees in certain compartments.

212

213 **Preprocessing of the Landsat time series**

214 Preprocessing of the Landsat time series consisted of atmospheric correction,
215 normalization, topographic correction, cloud masking and gap filling. A cloud free
216 image in 2001 was selected as a reference image, and it was atmospherically corrected
217 to a surface reflectance image using the Landsat Ecosystem Disturbance Adaptive
218 Processing System (LEDAPS), which utilizes a 6S radiative transfer model to correct
219 for atmospheric effects on a given date (Masek et al. 2006). Schroeder et al. (2006)
220 showed that the combination of atmospheric correction and normalization improved the
221 accuracy of spectral reflectance trajectory model compared with absolute correction.
222 Thus, all other Landsat images were normalized to the reference image using the
223 Iteratively Re-weighted Multivariate Alteration Detection (IR-MAD) algorithm (Canty
224 and Nielsen 2008). Then, C-correction (Teillet et al. 1982), was applied to all of the
225 images to remove topographic effects in the Landsat time series. Clouds and cloud
226 shadows were automatically masked using the FMASK algorithm (Zhu and Woodcock
227 2012). Subsequently, data gaps due to SLC and clouds were filled with a Weighted
228 Linear Regression procedure (Zeng et al. 2013) and the regression method proposed by
229 Helmer et al. (2010) using auxiliary Landsat images in the same year, respectively. The
230 combination of C-correction and Weighted Linear Regression procedure with regression
231 method was selected since this combination has shown to improve the accuracy of
232 forest disturbance detection in tropical forests using a Landsat time series (Shimizu et al
233 2016). Detailed descriptions of the C-correction and Weighted Linear Regression
234 procedure with the regression method can be found in Shimizu et al (2016).

235

236 **Forest change detection**

237 The LandTrendr algorithm (Kennedy et al. 2010) was applied to the Landsat
238 time series stack to detect forest changes. LandTrendr is a temporal segmentation
239 algorithm which fits straight line segments that capture the overall shape of the
240 trajectory, and in the process labelling each segment of disturbance and regrowth. A set
241 of parameters and a threshold value were used to divide a spectral trajectory into several
242 segments and to label each segment as either “disturbance” or “no-disturbance”. The
243 Normalized Burn Ratio (NBR) was selected to represent spectral trajectories in this
244 study because of its sensitivity to disturbance events (Kennedy et al. 2010; Grogan et al.
245 2015). We optimized the parameters and a threshold value to detect disturbances in this
246 region before running the entire study area. First, 133 disturbance and 331
247 no-disturbance samples were randomly collected. For each sample, the temporal
248 segmentation and labelling as either change or no-change were conducted using visual
249 interpretation.

250 Subsequently, we ran the LandTrendr algorithm for all combinations of
251 candidate parameters (Table 1), which were the same as those described by Kennedy et
252 al. (2010). Then, the results of LandTrendr were compared with that of visual
253 interpretation following Liang et al. (2014). Briefly, in each combination, the score was
254 calculated by summing the number of segment's vertices in the trajectories that were
255 successfully captured from LandTrendr compared with visual interpretation. Detailed

256 descriptions of this procedure are in Liang et al. (2014). The set of parameters that
257 achieved the highest score were determined to be the best (Table 2).

258 The threshold value to identify disturbance segments was set by choosing the
259 best threshold value that maximized producer's and user's accuracies for the change
260 class. Sliding the threshold values for all possible values, any segments whose
261 differences of NBR values exceeded the threshold value were labelled as a disturbance.
262 Then, producer's and user's accuracies of change class were calculated for each possible
263 threshold value (Figure 3). In this study, we selected the threshold value of 0.06, where
264 both producer's and user's accuracies were 95.45%. We proceeded with this calibrated
265 set of parameters and threshold value to perform disturbance detection for the entire
266 study area.

268 **Attribution of disturbance factors**

269 After running the LandTrendr algorithm for the entire study area with the best
270 set of parameters and threshold value, the attribution of forest disturbance agents to
271 either selective logging or other factors, as well as the accuracy assessment of forest
272 change detection, was implemented for the disturbance maps produced by LandTrendr.
273 In this study, we used the disturbance maps produced by the LandTrendr
274 trajectory-based analysis and the logging information from the Forest Department in
275 Myanmar to distinguish disturbances derived from selective logging from other
276 disturbances. We assumed that any disturbance that occurred in a certain forest

277 compartment during the selective logging year was derived from selective logging
278 activities. We also assumed that disturbances that occurred in a certain compartment in
279 other years (other than the selective logging year) resulted from other factors and not
280 from selective logging. In terms of the leaf-off condition of the forest and cloud cover,
281 we mainly used Landsat images acquired in December and January. This is due to the
282 fact that, in general, selective logging operations in Myanmar are completed by the end
283 of January, therefore it is believed that the above assumptions are reasonable. However,
284 other operations, such as skidding, could last until February. Further, some minor
285 disturbances caused by selective logging operations might be omitted from LandTrendr
286 detection, as indicated by Asner et al. (2002). In this context, we hypothesized the
287 existence of two types of errors regarding the attribution of forest changes: 1) omission
288 errors of any disturbance detection for the disturbance maps from LandTrendr; and 2)
289 misclassification of disturbances derived from LandTrendr as selective logging or other
290 disturbances during the attribution process.

291 The performance of disturbance detection was assessed using the samples
292 selected by a stratified random sampling strategy. We selected 150 pixels for each
293 no-disturbance and disturbance class from the disturbance maps produced by the
294 LandTrendr algorithm. Equal allocation of samples was selected since it gives the
295 smallest standard error (Olofsson et al. 2014). Then, each pixel was visually interpreted
296 by going through the Landsat time series as it was difficult to acquire an independent
297 dataset showing the yearly forest change in the entire study area. Finally, each pixel was

298 labelled as either no-disturbance or disturbance, and disturbance year was recorded
299 when the pixel was labelled accordingly. The overall, producer's and user's accuracies
300 were calculated using standard assessment procedures (Congalton 1991; Olofsson et al.
301 2014).

302 To detect errors associated with selective logging detection, we performed a
303 compartment-scale, rather than a pixel-based, analysis because of a lack of detailed
304 information of the logging operations at the pixel scale. Because the logging record
305 merely indicated the approximate locations of logging, it was impossible to determine
306 the exact locations of selective logging operations as a reference. Visual interpretation
307 was also prone to error because separating selective logging disturbances from other
308 disturbances is a difficult task using only Landsat data. So, there might be a minimum
309 of confounding factors of disturbance during its detection.

310 Alternatively, the relationships between the numbers of selectively logged trees
311 in certain compartments and the corresponding areas of disturbance in the same year
312 were investigated using 50 randomly selected compartments to show how many
313 omission errors existed. If LandTrendr successfully detects selective logging derived
314 disturbances, the disturbance areas detected by LandTrendr during the logging year
315 should have a significant correlation with the numbers of selectively logged trees in the
316 compartment. In addition, we calculated the disturbance area ratio, which is the ratio of
317 the disturbance area from LandTrendr to the total area of each compartment, during the
318 logging year, one year after logging, and in subsequent years before and after logging.

319 We hypothesized that if LandTrendr detected selective logging operations during the
320 logging year, the disturbance area ratio during the logging year should be significantly
321 higher than those of other years, and the disturbance area ratio should decrease in the
322 following year after the logging.

323

324 **Results**

325 **Attribution of disturbance agents**

326 The validation samples yielded an overall accuracy of 83.0% for disturbance
327 and no-disturbance pixels (Table 3). The omission error for the no-disturbance pixels
328 was 3.8%, which was smaller than the commission error (18.7%). Omission and
329 commission errors for the entire time series were 31.1% and 14.3%, respectively (Table
330 3). Most of the omission errors of disturbance resulted from samples omitted to the
331 no-disturbance pixels, and there were few samples that were misclassified as other
332 disturbance years.

333 Figure 4 shows the relationship between the total disturbance area derived from
334 the trajectory-based analysis and the numbers of harvested trees in each compartment
335 during the logging year. The disturbance area increased with increasing numbers of
336 harvested trees, and the correlation between these values was significant ($r = 0.37$, $p <$
337 0.05). However, in some compartments, in which there were logging operations, the
338 trajectory-based analysis did not detect any disturbances. Especially, the omissions of
339 logging operations between 2001 and 2003 caused a decrease of the correlation due to

the high omission error (Table 3). When we exclude the logging operation data between 2001 and 2003, the correlation increased from 0.37 to 0.50 ($p < 0.05$).

Figure 5 shows the disturbance area ratio in each compartment during the logging year, one year after logging and in other years. The mean disturbance area ratios during the logging year, one year after logging and in other years were 2.56%, 0.59%, and 0.53%, respectively. A multiple comparison of means showed that there was a significant difference in the mean disturbance area ratio between the logging year and other years ($p < 0.05$); however, the mean disturbance area ratio one year after logging was not significantly different from those in the other years ($p > 0.05$).

When summed, the results for the total areas of disturbance resulting from selective logging and other factors revealed that 4.7% of the study area was disturbed by selective logging and 5.4% of the study area was disturbed by other factors in the past 15 years. The largest disturbance occurred in 2010, while the largest disturbance resulting from selective logging occurred in 2011 (Figure 6).

Discussion

This study examined the accuracy of small scale forest disturbance detection, and it identified disturbances caused by selective logging operations in Myanmar forests using a trajectory-based Landsat time series analysis. The extracted validation samples for disturbance and no-disturbance pixels showed that there was a large omission error for disturbance detection (31.1%) and a lower commission error (14.3%). Most of the

361 omission errors in individual disturbance years were caused by the misclassification of
362 disturbances into no-disturbance pixels. In contrast, the omission errors in the
363 no-disturbance pixels were quite low (3.8%). Thus, it is assumed that the detected
364 disturbances in this area might be underestimated but only a few commission errors
365 were included.

366 The total disturbance area derived from the trajectory-based analysis in each
367 compartment for the logging year was significantly but weakly correlated with the
368 numbers of harvested trees in the corresponding compartment (Figure 4). This result
369 provides evidence of the capability of trajectory-based analysis to detect selective
370 logging operations in the Myanmar context. However, the trajectory-based analysis did
371 not detect any disturbances in some compartments in which logging operations occurred.
372 This result implies that some of the selective logging operations could not be detected
373 using these processing protocols. In this study, we assumed that any disturbances that
374 occurred in the same compartment during the logging year were caused by selective
375 logging. Thus, the detection errors stemmed from omission errors of selective logging
376 detection by LandTrendr or misclassifications of detected disturbances during the
377 attribution process. A multiple comparison procedure showed that the mean disturbance
378 area ratio, one year after logging, did not significantly differ from those in other years
379 (Figure 5). This result implies that few selective logging disturbances were misclassified
380 one year after logging operations. Thus, the omissions of selective logging operations in
381 Figure 4 mainly occurred because of limitations in the ability to detect subtle selective

382 logging disturbances in the trajectory-based analysis. We conclude that detected
383 disturbances were underestimated; however, the attribution of the detected disturbances
384 to selective logging or other factors was mostly accurate. Asner et al. (2002) reporting
385 on forest disturbance detection indicated that not all selective logging operations are
386 detectable using only Landsat data, and that the presence of a detected disturbance does
387 not necessarily correlate with the volume of wood removal, while ground damage
388 usually correlates with the harvested volume (Pereira et al. 2002). Our results also
389 showed that some of the selective logging disturbances were not detected. However, in
390 this study, the significant correlation between the detected disturbance area and the
391 number of harvested trees, albeit not strong, sheds light on the potential of the
392 applicability of trajectory-based analysis for logging detection, as it avoids the problems
393 associated with fast recoveries after logging, which prevent logging areas from being
394 located using standard processing protocols. The result suggest that trajectory-based
395 analysis can be an alternative way for detecting selective logging disturbances in the
396 tropics; however, caution should be exercised when detecting disturbances, always
397 being mindful of the detection errors.

398 The results of the attribution process showed that selective logging derived
399 areas and other factor derived areas accounted for 4.7% and 5.4%, respectively, of the
400 total study area. Finally, 10.1% of the total area was detected as disturbed in the past 15
401 years based on the methodology used in this study. These results imply the
402 human-induced disturbance area might be greater than the selective logging derived

403 disturbance area. Although there were a few commission errors resulting from
404 no-disturbance pixels being misclassified as disturbance pixels, disturbances resulting
405 from factors other than selective logging accounted for a substantial fraction of the total
406 disturbance area. With no supporting data at hand regarding this issue, we assumed that
407 these disturbances were human-induced. This is because there are relatively few natural
408 disturbances, such as fires and insect outbreaks, in this region, according to information
409 provided by local experts. Previous studies have indicated the emergence of illegal
410 logging in this region, although illegal logging cannot be quantified due to the lack of
411 sufficient data (Win et al. 2009; Mon et al. 2012). As Mon et al. (2012) showed,
412 selective logging does not cause deforestation or forest degradation at the low-level of
413 logging intensity implemented by the Myanmar Selection System. However, the
414 influence of factors other than selective logging on deforestation and forest degradation
415 is still unclear, and further studies are needed to identify the exact direct causes of these
416 disturbances and their impacts.

417 To our knowledge, this study is the first attempt to investigate the area affected
418 by selective logging in Southeast Asia using Landsat imagery time series and a
419 trajectory-based analysis. Annual disturbance detection could provide promising results
420 for detecting selective logging disturbances by avoiding the errors associated with fast
421 recovery after logging. This study shows the value of trajectory-based analysis for better
422 understanding disturbance detection and the characterization of its direct causes in the
423 tropics, although the detected disturbances should be cautiously interpreted, particularly

424 in situations where there is a lack of sufficient ground survey data, which are needed for
425 strict error assessments. Due to the fact that the disturbance area resulting from other
426 factors exceeded those resulting from selective logging, further studies should focus on
427 these other disturbances. Assessing direct impacts of human-induced disturbances, such
428 as illegal logging, over a vast area is a difficult task in the tropics; however, recent
429 developments in remote sensing, such as airborne Light Detection and Ranging
430 (LiDAR) or three-dimensional multispectral measurements, can be used to detect
431 small-scale disturbance agents over large areas. Applying these techniques to identify
432 the direct causes of disturbances may increase our understanding of forest changes in
433 this region.

434

435 **Conclusion**

436 Our study showed the utility of an annual Landsat time series combined with
437 trajectory-based analysis for detecting forest disturbances and characterizing their direct
438 causes in Myanmar. The overall accuracy for forest disturbance detection was 83.0% in
439 the study area. The areas affected by selective logging and other factors accounted for
440 4.7% and 5.4%, respectively, of the study area. The results showed that there were few
441 commission errors for disturbance detection but large omission errors for individual
442 disturbance year, indicating that the detected disturbances were underestimated. The
443 omitted disturbances were mainly misclassified as no-disturbance pixels both for all
444 disturbances and selective logging disturbances. While the trajectory-based annual

445 Landsat time series underestimated selective logging disturbances, the disturbance area
446 was significantly correlated with the numbers of harvested trees in each compartment
447 during the logging year. Thus we conclude that a trajectory-based annual Landsat time
448 series analysis is useful for selective logging detection in the tropics. A major constraint
449 of this study was the lack of available data regarding other forest disturbances. Further
450 studies complementary to this study should focus on identifying the direct causes of
451 disturbances other than selective logging, and their impact on future forest conditions.

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Table 1. Landsat images used in this study (Bold indicates main images).

Year	Sensor	year/month/day		
2000	ETM+	1999/12/30		
2001	ETM+	2000/11/15		
2002	ETM+	2002/2/5		
2003	ETM+	2003/1/23	2003/2/24	
2004	TM	2004/1/2		
2005	TM	2004/12/20		
2006	ETM+	2006/1/31	2006/1/15	2005/12/30
2007	TM	2007/1/10		
2008	ETM+	2008/1/5	2008/1/21	2007/12/20
2009	TM	2009/1/15		
2010	TM	2010/2/3		
2011	TM	2011/1/21		
2012	ETM+	2012/1/16	2011/12/31	
2013	ETM+	2013/1/18	2012/12/18	2013/1/2
2014	OLI	2014/1/13		

Table 2. Parameters and description tested values and selected values in this study

Parameter	Description	Values tested	Value selected
<i>despike</i>	Before fitting, if the difference of spectral value between before and after spike is less than 1- <i>despike</i> , the spike are weakened.	0.75, 0.90, 1	1
<i>pval</i>	The entire trajectory is considered no-change, if the <i>p</i> value of F-statistic calculated form the best fitted trajectory is higher than <i>pval</i> .	0.05, 0.10, 0.20	0.2
<i>max_segments</i>	The maximum allowable number of segments in fitting.	4, 5, 6	5
<i>recovery_thres hold</i>	The segment whose recovery rate is higher than 1/ <i>recovery_threshold</i> is not allowed.	0.25, 0.50, 1	1
<i>vertexcount_overshoot</i>	The potential vertices are identified until the number of segments reached the number set by the sum of <i>max_segments</i> and <i>vertexcount_overshoot</i> .	0, 3	3
<i>bestmodel_proportion</i>	A simpler model is chosen if its F-statistic exceeds <i>bestmodel_proportion</i> .	0.50, 0.75, 1	0.75

Table 3. Commission and Omission errors for LandTrendr change detection for 300 validation samples. (Overall Accuracy = 83.0%)

	Commission error (%)	Omission error (%)
No-disturbance	18.7	3.8
All disturbance	14.3	31.1
2000	50.0	25.0
2001	0.0	70.0
2002	0.0	57.1
2003	25.0	57.1
2004	7.1	23.5
2005	25.0	0.0
2006	15.4	23.5
2007	25.0	25.0
2008	15.4	21.4
2009	3.8	21.9
2010	0.0	25.0
2011	0.0	22.2
2012	0.0	75.0
2013	0.0	0.0

Figure captions

Figure 1. Location of Study area in Bago Mountains, Myanmar. The backgrounds of right and bottom-left figures display true color Landsat7 ETM+ image acquired on November 15, 2000. Administrative boundaries provided by Myanmar Information Management Unit (<http://www.themimu.info/>) were used as the township boundaries. World Borders Dataset provided by Thematic Mapping (<http://thematicmapping.org/>) were used as the country border.

Figure 2. Data processing flowchart in this study.

Figure 3. Producer's and user's accuracies of change class for threshold values in LandTrendr.

Figure 4. Relationship between the total disturbance area from the trajectory-based analysis and the total number of harvested trees in each compartment during the logging year.

Figure 5. Disturbance area ratio in each compartment during the logging year, one year after logging and in other years. Different letters indicate a significant difference ($p < 0.05$)

Figure 6. Areas of disturbance affected annually by selective logging and other factors from 2000 to 2013.

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