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Multi-resolution time series imagery for forest disturbance and regrowth monitoring in Queensland, Australia

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17 Abstract

18 High spatio-temporal resolution optical remote sensing data provide unprecedented opportunities
19 to monitor and detect forest disturbance and loss. To demonstrate this potential, a 12-year time
20 series (2000 to 2011) with an 8-day interval of a 30 m spatial resolution data was generated by
21 the use of the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) with
22 Landsat sensor observations and Moderate Resolution Imaging Spectroradiometer (MODIS) data
23 as input. The time series showed a close relationship over homogeneous forested and grassland
24 sites, with r^2 values of 0.99 between Landsat and the closest STARFM simulated data; and
25 values of 0.84 and 0.94 between MODIS and STARFM. The time and magnitude of clearing and
26 re-clearing events were estimated through a phenological breakpoint analysis, with 96.2 % of the
27 estimated breakpoints of the clearing event and 83.6 % of the re-clearing event being within 40
28 days of the true clearing. The study highlights the benefits of using these moderate resolution
29 data for quantifying and understanding land cover change in open forest environments.

30 Keywords: STARFM, BFAST, Landsat TM/ETM+, MODIS, Forest change, clearing, time
31 series, regrowth, data fusion

32

33 1. Introduction

34 Globally, forest loss and degradation is the second largest contributor to the post-industrial
35 revolution increase in atmospheric carbon dioxide (CO₂; van der Werf, et al., 2009). Whilst
36 much of the conversion from forest to non-forest (e.g., agriculture, urban areas, and

37 infrastructure) over the past four decades has been observed using satellite sensor data, losses
38 associated with degradation have been less discernable and consequently underestimated (Asner
39 et al., 2005). Uncertainties also remain regarding the contribution to carbon emissions.
40 Quantifying the extent and also magnitude of degradation is therefore important, particularly
41 given that affected areas often do not recover or are eventually cleared.

42

43 Many studies investigating ways to map forest disturbance have focused on changes in the
44 biophysical properties of forests, with these determined largely through the use of spectral data
45 or derived indices such as the Normalised Difference Vegetation Index (NDVI; Tucker, 1979).
46 For this purpose, and primarily because of the high temporal (near daily) coverage, coarse (~1
47 km) spatial resolution Advanced Very High Resolution Radiometer (AVHRR) and SPOT-
48 VEGETATION or Terra-1 Moderate Resolution Imaging Spectrometer (MODIS; 1 km to 250
49 m) have been used (Running and Nemani 1988; Schöttker, et al. 2010; Verstraete and Pinty
50 1996). In particular, these data allow for the detection of a) seasonal change (e.g. phenological
51 behaviour influenced by temperature and rainfall pattern), b) gradual change (e.g. impacts of
52 long term climatic or land management changes) and c) abrupt changes and disturbances (e.g.
53 land clearing or fire), as shown by Verbesselt et al. (2010). Finer (~ 30 m) spatial resolution data
54 from the Landsat sensors have allowed detection of specific events, such as vegetation clearing,
55 selective logging or fires (Kennedy, et al. 2009). These data have not though been widely used
56 for process monitoring because of the low temporal frequency (16 days for Landsat), which has
57 been reduced further by cloud cover, adverse atmospheric conditions and sensor problems
58 (Baumann, et al. 2011; Kennedy, et al. 2009). However, the release of the Landsat archive at no

59 cost (Wulder et al., 2012) has provided new opportunities for assessing historical changes in
60 landscapes.

61 To provide the option of high spatial resolution and high temporal frequency, a number of data
62 fusion techniques have been developed that link MODIS and Landsat sensor data (e.g., Gao et
63 al., 2006; Roy et al., 2008; Zhu et al., 2010). Of note is the Spatial and Temporal Adaptive
64 Reflectance Fusion Model (STARFM), which has been applied successfully for a range of
65 studies and purposes (Gao, et al. 2006; Hilker, et al. 2009a; Watts, et al. 2011). For example,
66 Walker et al. (2012) demonstrated the usefulness of the STARFM algorithm for phenological
67 studies in the drylands of Arizona by using 12 STARFM predicted images. Schmidt et al. (2012)
68 used STARFM to predict 333 Landsat sensor images over a 7.5 year time period, with these then
69 used to study regional ecological and phenological processes in a heterogeneous Northern
70 Australian savanna. ESTARFM (Zhu, et al. 2010) and mESTARFM (Fu, et al. 2013) have been
71 successfully applied as an improvement on STARFM, although findings of Emelyanova et al
72 (2013) are inconclusive in establishing whether this improvement is evident for all environments
73 (e.g., with a dominant temporal variance, STARFM gave a superior performance). Hence, the
74 less complex STARFM algorithm was applied here. Hilker et al. (2009b) used a STARFM-based
75 fusion model (STAARCH) for mapping forest disturbances. This algorithm computes a
76 Disturbance Index (DI) based on a Tasselled Cap (Kauth & Thomas, 1976) transformation and
77 NDVI data for each simulated image. A regionally adapted mask of mature forest is then used to
78 scale and empirically threshold the DI time series. The pixel neighbourhood is included to reduce
79 DI noise.

80

81 An environment where the STARFM algorithm has not been evaluated is the open forests and
82 woodlands of northern Australia (Williams et al., 1997; Schmidt, et al. 2012, Bhandari, et al.
83 2012). Nevertheless, temporal comparisons of Landsat imagery have been undertaken to allow
84 detection of forest loss. In particular, the Queensland Department of Science Innovation
85 Technology and the Arts (DSITIA) developed a program to monitor vegetation change using
86 Landsat data; the Statewide Landcover and Trees Study (SLATS). In this programme, annual
87 state-wide maps of Foliage Projected Cover (FPC) have been generated using empirical
88 relationships between ground-based estimates from a range of vegetation types and both Landsat
89 data and climate variables (Armston, et al. 2009, Danaher et al, 2010). From these data, forest
90 losses have been reported annually since 1999 and over longer time intervals between 1988 and
91 1999 (Danaher et al, 2010). The scale of the Landsat scale imagery has also proved adequate for
92 describing the complex and spatially heterogeneous landscapes occurring across the state
93 (Danaher, et al. 2010). In this case, images captured during Queensland's dry season are
94 preferentially selected, as these give best differentiation between the dry ground cover layer and
95 the non-deciduous woody vegetation.

96 To evaluate the potential application of the STARFM algorithm for determining undisturbed
97 forest phenology and detecting and spatially differentiating the date and magnitude of forest
98 change, a 12-year time series (2000 to 2011; with an 8-day interval) of Landsat and STARFM
99 simulated images was used. The study was conducted in the Injune Landscape Collaborative
100 Project (ILCP) research area west of Injune in central southeast Queensland. A major benefit of
101 using this area was that large scale (< 1:4000) true colour aerial photography and Light Detection
102 and Ranging (LiDAR) data were acquired in 2000 and 2009 over a well-defined grid of 150 500

103 m x 150 m Primary Sampling Units (PSUs), with 4 km between each in the north-south and east-
104 west directions. Hence, these data could be used to establish reference sites that had experienced
105 limited change as well as disturbance and regeneration at the stand level over the period of the
106 time-series. The study sought to establish whether a) a baseline of vegetation phenology over the
107 12 year period could be described for undisturbed natural vegetation based on the NDVI, b)
108 time-series analysis could be used to indicate the timing and magnitude of disturbance events,
109 and c) an increasing trend in NDVI metrics (e.g., dry season minima) could be associated with
110 the regeneration of forests.

111 2. Study area

112 The study focused on the ILCP research area, which is located approximately 100 km west of the
113 township of Injune in central southeast Queensland (Figure 1a, b). The landscape can be
114 described as a southern savanna region characterised as having variable rainfall and an
115 ecosystem that is generally water limited. The majority of the landscape consists of forests and
116 agricultural lands, with some abandoned to regrowth. Scattered buildings (primarily
117 farmhouses) and unsealed roads are the main urban infrastructures occurring. The 37 x 60 km
118 area was selected for the initial study as extensive tracts of vegetation were being cleared in the
119 late 1990s and the open forests and woodlands (wooded savannas) contained structural
120 formations typical to many occurring in Queensland. The study area was divided into a large
121 sample grid of 150 (10 columns x 15 rows) Primary Photo Plots (PPPs; Figure 1c) over which
122 large-scale 1:4000 aerial photographs were acquired in 2000. Within these, 500 m x 150 m PSUs
123 (Figure 1d) were located in the stereo overlap. Each PSU was further divided into 30 secondary
124 sampling units (SSU) of 50 m x 50 m. The original study area was chosen to be at the centre of

125 the Landsat satellite swath (Tickle, et al. 2006), but was extended south by 20 km to include
126 areas where a range of land clearing activities were occurring.

127 Between 2000 and 2011, changes in the structure, biomass and species composition of forests
128 occurred within the study area. Changes were caused by natural events such as fires, and human
129 activities including stock grazing, selective and complete tree clearing by landholders (primarily
130 for agricultural purposes) (Goodwin and Collett, 2014). Changes in climatic conditions (e.g.,
131 drought and flooding) also impacted on the structure and composition of forests. For example, in
132 2006, many large and mature rough barked apple (*Angophora floribunda*) trees died as a
133 consequence of a prolonged period of drought, but smooth barked apples (*A. leiocarpa*) were
134 unaffected (Lucas, et al. 2008). Regrowth following clearing for agriculture or fires was also
135 commonplace.

136 FIGURE 1 near here, please.

137 3. Data and methods

138 3.1 Spaceborne, airborne and field data

139 For the ILCP study area, 97 Landsat sensor data with a cloud cover of less than 20 %, acquired
140 from December 1999 to September 2011 were obtained, with 69 and 28 acquired by the Landsat
141 Thematic Mapper (TM) and Enhanced TM (ETM+) respectively (Table 1a). The Scan Line
142 Corrector (SLC)-off effect (which results in missing data in alternate groups of lines at the edge
143 of the image) was evident within 11 ETM+ scenes (Pringle et al. 2009). For the same period,
144 525 MODIS images were available from which the MODIS Bidirectional Reflectance

145 Distribution Function (BRDF) model parameters (MCDS43A1) and the BRDF/Albedo quality
146 product (MCD43A2) had been derived. The latter is a quasi-roll-on version of the 16-day
147 MODIS composites and is produced every 8 days (Roy et al., 2008).

148 TABLE 1 near here, please.

149 Across the PSU grid, discrete return LiDAR (using an OPTECH ALTM1020) and 1:4000 scale
150 colour aerial photographs had been acquired in 2000, with a repeat coverage colour aerial
151 photographs and full waveform (RIEGL LMS-Q560) LiDAR obtained in 2009. Flight height and
152 pulse densities were 150 m and 1 pulse per m² in 2000 and 400 m and 4 pulses per m² in 2009.
153 Both LiDAR datasets were processed to a 1 m spacing. These data were used to obtain estimates
154 of height and cover for each PSU for the years 2000 and 2009 based on the methods outlined in
155 Tickle et al. (2006). A comparison of these data allowed areas that had remained undisturbed or
156 otherwise to be identified. Through interpretation of the 2000 aerial photography, forest types
157 were delineated and assigned with a community code, with these representing the primary
158 dominant, co-dominant and/or sub-dominant tree species or genera. The interpretation of these
159 data was assisted by forest inventory data collected in 2000 from selected (34) 50 m x 50 m
160 SSUs located within the PSU grid (Tickle et al., 2006), with this including measures of
161 vegetation structure (cover, height and diameter distributions) and species type. More limited
162 field campaigns were conducted in July 2006 (to collect information on species composition
163 from a range of SSUs) and April 2009 (during which forest inventory data were collected from 6
164 SSUs that had been inventoried in 2000 and from additional sites within selected SSUs).

165

166 3.2 Data pre-processing

167 To guarantee the radiometric consistency of the Landsat sensor data, the algorithm outlined by
168 Flood et al. (2013) to derive standardised surface reflectance for Landsat TM and ETM+ imagery
169 was applied and BRDF-adjusted reflectances were then calculated based on a solar-zenith angle
170 of 45°. All Landsat sensor data were screened for cloud and cloud shadow using an automated
171 masking approach (Zhu and Woodcock, 2012) with manual refinement. MODIS BRDF-adjusted
172 reflectances, also with a solar zenith angle of 45°, were derived using the Ross-Thick Li-Sparse
173 reciprocal BRDF model and the parameters derived from the MCD43A1 model. The MODIS
174 quality product (MCD43A2) was applied rigorously such that only those pixels associated with a
175 ‘good’ or ‘very good’ BRDF inversion were used in subsequent analyses.

176 3.3 Generation of time series datasets

177 For each date of MODIS image acquisition, a prediction of reflectance at moderate spatial
178 resolution was made using the STARFM algorithm (Gao et al., 2006). The STARFM algorithm
179 simulates pixel values based on spatial weights determined by regional statistics between
180 spectrally similar medium resolution Landsat and coarse resolution MODIS image pairs.
181 Changes in reflectance in the coarse resolution MODIS images are applied to the fine resolution
182 Landsat image. The algorithm produces a synthetic image from base pairs of Landsat and
183 MODIS images at the time t_0 and a MODIS image at the prediction time t_k . STARFM was run
184 in the mode of using two base pairs at t_0 and t_{k+x} . By applying the algorithm over the period
185 2000-2011, an 8-day temporal series of moderate (i.e, 30 m) spatial resolution BRDF adjusted
186 reflectance data was generated (Table 1b). The Landsat 7 ETM+ data were for the time period

187 December 1999 to May 2003 but, thereafter, Landsat 5 TM data were used in preference as data
188 line drop outs associated with the SLC-off effect reduced the reliability of predictions using the
189 STARFM algorithm. To avoid spatial data gaps, no two consecutive Landsat 7 ETM+ images
190 with the SLC-off effect were used (Figure 2).

191 FIGURE 2 near here, please.

192 NDVI time series data of the simulated dataset and MODIS were compared to the Landsat sensor
193 data acquired. To confirm the consistency of the time series datasets for different ecological
194 situations, NDVI trajectories for two homogeneous regions at the MODIS scale were calculated
195 and compared. The regions were a 1.5 km x 1.5 km forested area (R1) and a 1 km x 1 km
196 formerly cleared (between 1988 and 1997) grassland area (R2; identified in Figure 3b). The time
197 series of NDVI was smoothed using the Savitzky-Golay filter with a length of 5 to reduce noise
198 but still expose abrupt change events that might occur in the series (Jönsson and Eklundh, 2004).
199 Figure 3 (a-c) depicts the spatial details of a Landsat 5 image (a) and MODIS image (b) used to
200 simulate a STARFM image (c) for the date of the MODIS image. Figure 3(d) displays spatially
201 the SLATS clearing eras. A reference grid showing the PSUs is also overlain (Figure 3a).

202 FIGURE 3 near here, please.

203 3.4 Establishing reference data

204 The floristic composition of the landscape was determined by summarising the occurrence of
205 species within each of the 4500 SSUs, as determined from aerial photograph interpretation
206 (Tickle, et al. 2006). Tickle et al. (2006) developed a system of three-letter symbols for species

207 description in the region, which was adopted in this study. The major species in the region were
208 Brigalow (*Acacia harpophylla*; BGL), Cyprus pine (*Callitris glaucophylla*; CP-), Poplar Box
209 (*Eucalyptus populnea*; PBX), Rough-barked Apple (*Angophora floribunda*; RBA), Silver-leaved
210 Ironbark (*Eucalyptus melanaphloia*; SLI), Smooth-barked Apple (*Angophora leiocarpa*; SBA),
211 Sandalwood Box (*Eremophila mitchellii*; SWB), Tumbledown Gum (*Eucalyptus dealbata*;
212 TDG), Gum-topped Box (*Eucalyptus dura*; GTI) and various *Eucalyptus* species (EUS).
213 Approximately 70% of the dominant species were CP-, SLI, SBA and EUS. However, pure
214 stands of particular species were rare, and these same species were also co- or sub-dominant.
215 The most frequent associations (representing 31% of the total) were PBX and SWB communities
216 (termed PBXSWB) and CP- and SLI or SBA with either dominating (i.e., CP-SLI, SLICP-, CP-
217 SBA, SBACP-).

218 For each of the SSUs, estimates of maximum stand height (m) and cover (%) were generated
219 from the LiDAR data acquired in 2000 and 2009 and using the algorithms outlined in Tickle et
220 al. (2006) and Lee and Lucas (2007). SSUs that had experienced changes (or otherwise) were
221 identified by comparing these LiDAR-derived products. SSUs associated with minimal change
222 (i.e., < 20% of both median height and cover) were assumed to be comparatively 'stable'. In each
223 case, this was confirmed by referring to the aerial photography acquired in the same two years,
224 with these being of sufficient spatial resolution to resolve individual tree crowns and the growth
225 and loss of individual plants or clusters of vegetation. SSUs that had experienced more than a
226 20% change in height and cover were assigned to a change category (degradation, clearing or
227 regrowth) with the causes and nature (i.e., natural or anthropogenic) of change events and
228 processes (e.g., fire, clearing for agriculture, selective logging, grazing) also established through

229 reference to the time series of aerial photography and other imagery available for the ILCP area.
230 Where regeneration occurred between 2000 and 2009, the species composition of the
231 regenerating forests was observed (in the field) to be different (in some cases) from that of the
232 pre-cleared/degraded vegetation. Hence, a species code was unable to be assigned with
233 confidence except in the case of BGL which was distinguishable in the 2009 aerial photography
234 by its visual appearance (typically silver-blue in crown colouration) and spatial arrangement (a
235 high density of individuals on previously cleared land).

236 3.5 Time series data analysis

237 NDVI time series values were extracted from the STARFM data and spatially averaged for each
238 SSU. A time series break-point analysis was performed by applying the Breaks for Additive
239 Seasonal and Trend (BFAST) algorithm (Verbesselt et al., 2010), with this used to establish
240 where vegetation disturbance (e.g., through clearing for agriculture, logging or fire) occurred.
241 The BFAST algorithm integrates an iterative decomposition of the additive components of trend
242 (T), seasonality (S) and remainder components (noise; e), with abrupt, gradual, and seasonal
243 change detected. Therefore, BFAST separates temporal variability from phenological change and
244 performs a phenological change detection (Verbesselt et al., 2010). The model fits a piecewise
245 linear trend and seasonal model and is of the form:

$$246 \quad Y_t = T_t + S_t + e_t \quad \text{Equation (1)}$$

247 where the time-steps t range from 1 to n . Through this approach, the most significant change
248 event in the time-series is located.

249 3.6 Temporal data validation

250 To validate the timing and magnitude of the clearing events, reference was made to the SLATS
251 annual forest clearing data layers. These raster layers, which report clearing annually since 1999,
252 were segmented into spatially coherent clusters, which were then assigned a time and magnitude
253 of the clearing event as identified using BFAST (based on the most significant breakpoint in the
254 time-series). The confidence interval around the clearing date was also assigned.

255 Further validation was performed using the full time-series, including imagery that were not used
256 within the STARFM algorithm or supported variable amounts of cloud cover. Using these data,
257 the clearing events that occurred were interpreted visually for each SSU that intersected the
258 SLATS clearing layers. Each SSU was then associated with the last image date before clearing
259 and the first thereafter. The same procedure was applied for areas of potential re-clearing. The
260 confidence intervals around the breakpoint estimates of BFAST were compared and intersected
261 with the “true” clearing interval to obtain a validation for the temporal clearing estimate.

262 3.7 Identification of vegetation regrowth

263 After a clearing event, an increase in the NDVI might be expected as foliage and canopy cover
264 increases over time. To establish whether this occurred, the time series data were divided into
265 annual cycles starting with the end of the dry season (determined as November 1st) to the onset
266 of the wet season in the following year (October 31st). For each cycle, a dry season minimum
267 NDVI map was generated, with this typically associated with the driest conditions where all
268 remaining greenness in the deciduous savannah was attributable to woody vegetation (i.e., the

269 non-grass layer). Trend lines in the minimum value of the NDVI for the duration of the time
270 series were then used to establish trends in relation to forest growth.

271 4. Results

272 4.1 8-day STARFM generated data

273 The STARFM data generated from coarse spatial resolution MODIS and Landsat sensor data
274 provided a similar representation of the spatial characteristics of the forest and agricultural
275 elements within the landscape (Figure 3a-c). Comparisons of the red and near infrared
276 reflectance recorded by the Landsat sensor (1st June 2004) and simulated using the STARFM
277 algorithms also indicated a close correspondence (Figure 4); the Landsat image was not used in
278 the STARFM data simulations.

279 FIGURE 4 near here, please.

280 In general, the time series behavior of the NDVI between the MODIS and the STARFM
281 predictions showed a close correspondence (Figure 5) for the two test regions R1 and R2, with
282 these representing the forest and grassland site respectively. In Figure 5, it is evident that a very
283 different phenology and trend would be provided if Landsat sensor data alone were used
284 (examples within the dotted lines). This is particularly the case regions with rainfall limited
285 vegetation growth e.g. in savanna regions where vegetation phenology is driven by highly
286 variable rainfall.

287

288 FIGURE 5 near here, please.

289 In some cases, NDVI values derived from the original Landsat data tended to be higher or lower
290 during periods of seasonal minima or maxima respectively compared to MODIS NDVI values,
291 particularly for the grassland site (e.g., in 2001). These differences were most likely due to the
292 coarser spatial resolution of the MODIS data and the sampling procedure within the STARFM,
293 which can result in removal of extreme values and alterations of averaged values at the Landsat
294 scale. Some gaps were evident in the MODIS data (one for R1 and two for R2), which were
295 identified as ‘bad’ values in the MODIS quality flag files. The correlations (r) between the
296 MODIS and STARFM time series for Regions 1 and 2 were 0.92 and 0.96 respectively ($r^2 =$
297 0.84 and 0.94), with root mean square error (RMSE) values of 0.026 and 0.031. The correlations
298 between the Landsat and the closest STARFM simulated data were 0.996 for both the forested
299 and grassland site (r^2 of 0.992), with an RMSE of 0.006 and 0.011 respectively. The residuals of
300 this comparison ($NDVI_{Landsat} - NDVI_{STARFM}$) are shown in Figure 6; the closed STARFM
301 image date closest to the respective Landsat scene was selected. It is noticeable that the RMSE is
302 higher for Region 2 despite the correlation being similarly quite high with this attributable to the
303 higher range of the NDVI.

304 FIGURE 6 near here, please.

305 A few outliers were observed with these being mainly associated with smoke plumes caused by
306 bush-fires that were not included in the cloud masks.

307

308 4.2 Forest and land cover dynamics within the ILCP

309 Comparison of the LIDAR data from 2000 and 2009 indicated that 58% of PSUs experienced no
310 significant changes in height or cover and were regarded as relatively stable over this period.
311 These communities included those dominated or co-dominated by CP-, SLI, SBA, PBX, SWB,
312 TDG or EUS (i.e., codes CP-SLI, CP-SBA, SLICP-, SBACP-, PBXSWB and PBXTDG and
313 EUS); Table 2. Increases in both median height and cover of > 20% were evident within 12% of
314 the PSUs, with losses occurring in 8%. Areas of regrowth were associated with PSUs where at
315 least 20% of the contained SSUs showed more than a 20% increase in median height and cover.
316 As an example, in PSU 108, an area of about 3 hectares experienced an increase of 2-6 m in
317 height between 2000 and 2009, as determined through time series comparison of LiDAR data
318 (Figure 7). Within the regrowth communities, PBX and BGL were dominant although in the
319 former case, a greater mix of other species (e.g., SWB) occurred. Forests that were cleared
320 between 2000 and 2009 included those dominated by PBX and co-dominated by CP- and SLI
321 (CP-SLI; 1 SSU) whilst more areas had regenerated following extensive clearing in the period
322 leading up to 2000 (Table 3). A further 12% had experienced some level of change (whether
323 positive or negative) and 10% remained deforested through the period.

324 FIGURE 7 near here, please.

325 TABLE 2 near here, please.

326

327

328 4.3 NDVI Trajectories

329 4.3.1 Stable forests

330 For relatively stable forest areas, defined using the time-series of LIDAR data, differences in the
331 magnitude of mean Landsat-derived FPC varied as a function of species mix (Table 4), ranging
332 from 30.4 to 48.0; the deviation over the period 1999 to 2008 was, at most, 2.2 %. This
333 indicated that the majority were in the open forest category. Furthermore, trends in NDVI were
334 similar for the communities considered, with these mainly differing in magnitude, as illustrated
335 in Figure 8a and b. The low points in the time series were associated with a comparative lack of
336 rainfall.

337 TABLE 3 near here, please.

338 TABLE 4 near here, please.

339 Despite comparatively lower canopy cover (as reflected in the FPC values), the highest values in
340 the NDVI were associated with forests co-dominated by TDG and SBA. The lowest trending
341 NDVI was associated with communities co-dominated by CP- and SLI, with the needle-like
342 leaves of the former being of low greenness despite a high FPC.

343 FIGURE 8 here, please.

344 In all cases, the NDVI rarely varied by more than 0.2 overall and no more than 0.1 from the
345 mean value. Whilst the NDVI trends for PBXTDG and EUSCP- were without major deviation
346 from the time series mean, those associated with SBACP- and CP-SBA exhibited some

347 anomalies with deviations greater for CP-SBA in January-February in 2004, 2008 and
348 particularly in 2010.

349 4.3.2 Clearing of forests

350 For disturbed vegetation, a rapid decrease in the NDVI was observed immediately following the
351 disturbance event. Two examples are given in Figure 9 a) relative to the stable vegetation
352 trajectory, where a clearing event occurred in PSU 108 in late 2000 in an area containing a mix
353 of CP-, SLI and EUS (CP-SLIEUS), and PSU 68 in 2002 (dominated by PBX). Figure 9 b) and
354 c) illustrate the automatic breakpoint detection in the STARFM-based NDVI time series.

355 Estimates of the date of clearing as well as the confidence interval and the magnitude of the
356 event are displayed graphically in Figure 9 b) and c). Prior to the clearing events, the mean
357 temporal signature was similar to that of vegetation that had experienced minimal disturbance.
358 After the event, the behaviour changed dramatically, initially following a trend more typical of
359 grasslands (high NDVI amplitude and narrow low frequency). However, as the regrowth matured
360 towards 2011, the signature became more similar to that of stable vegetation. The slopes of the
361 fitted trend line after the clearing events were 0.015 for PSU 108 and 0.022 for PSU 68 (over
362 ~10 year period). As a consequence of clearing forest vegetation, a drop in NDVI from 0.61 to
363 0.26 and from 0.44 to 0.28 was observed for these PSUs respectively. In both cases, the change
364 event was detected with BFAST (Verbesselt, et al. 2010; Figure 8b and c) and was estimated to
365 be 16th November 2000 and 29th August 2002 respectively.

366 FIGURE 9 near here, please.

367

368 4.3.3 Regenerating vegetation

369 In several areas, vegetation clearing occurred prior to the earliest date of the study period. The
370 comparison of NDVI values for non-forest and forested areas, estimated for the date associated
371 with the seasonal minima, indicated relative stability. However, the seasonal minimum NDVI for
372 regrowth areas progressively increased for PSUs 68 and 108 (Figure 10). In most areas, regrowth
373 was dominated by BGL or PBX mixed with other species (e.g., SWB, SLI) within the
374 community.

375 FIGURE 10 near here, please.

376 4.5 Temporal validation

377 All clearing events could visually be identified to within a maximum of 60 days of any two
378 consecutive Landsat acquisitions (using all available images). Figure 11 visualises the clearing
379 and re-clearing data. The first date of the validation interval (i.e. before clearing) is plotted as
380 base value (zero) and the other data points relative to this: clearing validation interval, the
381 BFAST breakpoint estimate and confidence interval for each SSU. Clearing and re-clearing were
382 evaluated separately in Figure 11a) and b).

383 The different width on the data population of the validation intervals and breakpoint confidence
384 intervals is visible as are the events where the intervals are not intersecting (as difference in
385 days).

386 FIGURE 11 near here, please.

387 The one large outlier (>200 days) in Figure 11b) could be identified as a gully that did not burn
388 in a fire in September 2003 (like the other data points of this PSU) so that a later, non-clearing
389 event was attributed as the event with the most significant change in BFAST.

390 The number of SSUs (%) where the breakpoint confidence interval intersected with the
391 validation interval is show in Table 5, with this being 65.8% for clearing and 81.2 % for re-
392 clearing. As the NDVI time series was filtered using a Savitzky-Golay filter, the analysis was
393 repeated but increasing the confidence interval by one time step (8 days). In this case, 94.9%
394 and 92.5 % of the intervals intersected for the clearing and re-clearing states respectively. This
395 indicated that the majority of the clearing date was estimated as being close to the actual clearing
396 event. In the case of a well-defined, sharper NDVI drop in the time series, the confidence
397 interval was generally smaller (see also Figure 9). The confidence intervals for the primary
398 clearing were substantially smaller than for the re-clearing events (Table 5).

399 TABLE 5 near here, please.

400 As a clearing event can be at either end of the validation interval (1st day after the interval start
401 or the last day before the interval end), a “best case” and a “worst case” was calculated as a
402 minimum and maximum time difference between the interval end points (validation interval and
403 breakpoint confidence interval). The median of the minimum absolute difference between the
404 intervals (best case) is 1 time step or 8 days; the maximum is 8 time-steps or 64 days. For the
405 worst case, 96.2 % of the estimated breakpoints of the clearing event and 83.6 % of the re-
406 clearing event were within 40 days of the true clearing (Table 6).

407 TABLE 6 near here, please

408 4.7 Spatio-temporal Visualisation

409 The time and magnitude of the clearing events are visualised in Figure 12. Figure 12a) shows the
410 date of the first significant breakpoint between February 2000 and September 2009 for each
411 clearing and potential re-clearing area as mapped in the SLATS clearing eras. The associated
412 magnitude of change (in NDVI units) is provided in Figure 12 b) for comparison.

413 Figure 12 near here please.

414 5. Discussion

415 5.1 8 day STARFM data

416 As shown also by Schmidt et al. (2012) and Bhandari et al. (2012), the STARFM algorithm was
417 found to produce good interpolated time-series (8 day frequency over a 12 year period) of the
418 NDVI, with these representing the vegetation dynamics in this Australian environment. Spatial
419 averages of Landsat, MODIS and STARFM data over homogeneous forest and grassland sites at
420 1.5 km x 1.5 km and 1 km x 1 km respectively were also similar (see Figure 5). However, high
421 and low NDVI values in the time series were lower within the MODIS data compared to the
422 Landsat and STARFM data. This was most evident in the grassland area and the forested site
423 during the wet season of 2000/2001 and may be related to the spatial scale difference of the
424 MODIS 500 m and the 30 m Landsat data as high and low values are often averaged when
425 moderate spatial resolution data are fused with coarser resolution data.

426

427 The high repeat frequency data of the STARFM application provides new and important
428 information on land use and vegetation dynamics that cannot be obtained from other sources.
429 Whilst applied to a small study area in this case, there is the potential for application across
430 larger areas including the state of Queensland (88 Landsat footprints). However, processing
431 times and data storage may be limiting factors and reducing the temporal frequency to 16 day or
432 monthly time-steps should be considered. Spatial interpolation methods (e.g., Pringle et al.,
433 2009) also need to be considered to account for the SLC-off effect and prevent significant data
434 gaps. Potential improvements to the prediction might result from the application of improved
435 versions of the STARFM algorithm (Zhu et al., 2010; Fu et al., 2013). Whilst not considered in
436 this study, other standardized vegetation indices derived from fractional cover estimates might
437 also be used (Scarth, et al., 2010; Schmidt and Scarth, 2009).

438 5.2 Change detection

439 Across the ILCP, a number of PSUs were associated with stable vegetation, as identified by
440 referencing time-series of LIDAR and aerial photography. Within these stable areas, the NDVI
441 fluctuated largely in response to rainfall, with the upward trend from the mid 2000s onwards
442 attributable to recovery from the intense drought of 2006. In these evergreen environments, the
443 dry season component is often contributed by the overstorey component and so the NDVI within
444 intact vegetation increase may reflect the processes of woody thickening. The recommendation is
445 that trajectories from these stable sites be used as reference against which to assess the
446 vegetation response in different ecosystems, bioregions or climate zones. This would allow, for
447 example, investigations into management impacts on forest response and provide a reference

448 dataset for ecosystem functionality that may be linked to biodiversity indicators or land cover
449 dynamics (Bastin, et al. 2012; Carroll, et al. 2011).

450 Outside of the stable areas, a wide range of changes has occurred within the ILCP. These include
451 the complete clearing of vegetation so that land can be used for agriculture, re-clearing of
452 regrowth and partial clearing through selective logging (primarily of CP-). Changes induced by
453 natural events were largely associated with fires (e.g., in 2003, 2010 and 2011 after wet years
454 with sufficient understorey fuel accumulation). Other processes leading to loss of forest cover
455 include the natural competition and succession of trees, although tree dieback was also
456 associated with the periods of drought. Extensive areas of regrowth on land previously cleared
457 or subject to fire were also observed. Much of the regrowth was dominated by one or several
458 species (e.g., BGL, PBX). Such changes were often not detected by comparing annual satellite-
459 derived maps of forest and non-forest, but the use of hyper-temporal actual and simulated
460 Landsat sensor data provided an opportunity to identify specific events and/or processes relating
461 to disturbance and regeneration. Seasonal minimum NDVI shows a close correspondence to
462 annual FPC as shown by Schmidt, et al. (2012) and thus provides the best option for quantifying
463 land cover transitions as the influence of ephemeral vegetation is reduced.

464 Whilst change is best detected when observed directly by the Landsat sensor, either just before or
465 after the event, the STARFM products are beneficial. In particular, the integration of the high
466 temporal resolution information from the MODIS with the finer spatial resolution Landsat
467 imagery in a time-series allows a better description of the phenological changes that are
468 occurring. Indeed, some changes can only be identified when the temporal context is given. The
469 parameters of the BFAST algorithm can also be set to identify multiple change events

470 (Verbesselt et al., 2010), with the number, time and magnitude being of particular relevance for
471 natural resource management. By also tracking the temporal signal, the regeneration of forests
472 can be observed and rates determined with different time segments of the seasonal minima of the
473 NDVI being useful for mapping different land cover transitions. The time-series data may be
474 used to detect clearing and clearing of regrowth; and might assist in speeding up the compliance
475 process and reduce uncertainties (Goulevitch, 2012).

476 Maps showing the time of the clearing event and the magnitude of the NDVI change are
477 displayed in Figure 12. All areas labelled as cleared in Figure 3d), including potential re-
478 clearing sites, were investigated. A prior knowledge of clearing was used in this approach and
479 BFAST allowed the most significant change event in the time-series to be detected. The primary
480 clearing event could be identified with a high degree of accuracy but re-cleared areas were less
481 able to be detected.

482 5.3 Validation

483 For validation of change, the full time-series of Landsat sensor data was used as ground-based
484 data or aerial photographs for the clearing date were not available. The maximum length of time
485 between any two Landsat data acquisition was 60 days. These intervals were intersected with the
486 confidence intervals around the breakpoint estimates from BFAST.

487 SSUs were treated as independent observations. It could be argued that the analysis should be
488 performed on a PSU basis to reduce the spatial dependency, but the sample appeared to be not
489 large enough to derive statistically meaningful statements based on a summarised PSU basis.

490 State-space models which explicitly take the spatial context into account might overcome this,
491 but are generally computationally quite expensive.

492 6. Conclusions

493 An 8-day interval time series of STARFM generated data based on 525 MODIS and 97 Landsat
494 images was generated for a period of 12 years and with a time-interval of 8 days. The
495 correlations between the MODIS and STARFM time series were 0.92 and 0.96 ($r^2 = 0.84$ and
496 0.94) for a homogeneous forested and grassland area respectively. The correlations (r and r^2)
497 between Landsat and the closest simulated STARFM data were 0.99 in all cases. The hyper-
498 temporal NDVI time series were suitable for detecting primary clearing events with 94 %
499 accuracy within 40 days of a clearing event. The minimum NDVI within this time series was
500 also used to track regrowing vegetation. For stable areas of vegetation, identified using temporal
501 LIDAR data, the NDVI reflectance trajectories were variable and different in magnitude but
502 trends were similar. The study highlighted the benefits of using STARFM generated data for
503 observing and quantifying trends in vegetation dynamics with potential applications for land
504 management and forest conservation.

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508

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627

628 Figure captions:

629 Figure 1: a) and b) The location of the Injune study area in Queensland, the dotted lines in c)
630 indicate approximately the centre of the Landsat ETM+ swath unaffected by the SLC-off effect.
631 d) the arrangement of the Primary Photo Plot (PPP), Primary Sampling Units (PSU) and
632 Secondary Sampling Units (SSU) and the layout of the sampling grid.

633 Figure 2: The distribution of Landsat TM (black) and ETM+ (grey) images available for the
634 ILCP area and used as input to the STARFM simulations.

635 Figure 3: July, 7 2011 data (red band reflectance) of the ILCP research area: a) Landsat TM; b)
636 MODIS, July, 12 2011; and c) STARFM simulated image also July, 7 2011. d) The Statewide
637 Land Cover and TreeS (SLATS) map of clearing by year. The PSU grid is overlaid in a), in b)
638 are two homogeneous forest (R1) and grassland sites (R2) marked.

639 Figure 4: Scatterplots of band 3 and 4 for Landsat 5 TM and STRAFM image of the same date:
640 June 1, 2004. The Landsat image was withheld from the utilisation in the STARFM predictions.
641 The dotted red line represents the 1:1 line, the data points are a 10% random sample across the
642 study area.

643 Figure 5: MODIS, Landsat and STARFM NDVI time series data for homogeneous regions a) a
644 1.5 km x 1.5 km forested area (R1; see Figure 3) and b) a 1 km x 1 km grassland area (R2; see
645 Figure 3). The vertical dotted lines indicate intervals where the phenological signal would differ
646 with Landsat imagery alone.

647

648 Figure 6: Residual plot for R1 a) and R2 b) of all Landsat (TM/ETM+) NDVI data and the
649 closest simulated STARFM NDVI image. The dotted line represents one standard deviation.

650 Figure 7: The processes of clearing and regrowth observed by comparing LiDAR height data
651 acquired in 2000 and 2009 (for PSU 108) both a) in plan view and b) in profile. The dashed
652 white line in the 2009 image plots the transect of the profile data.

653 Figure 8: a) Time-series of the NDVI for stable vegetation (determined through interpretation of
654 high resolution airborne sensor datasets) showing the mean and standard deviation for the period
655 2000-2012. A general increase with monthly rainfall (mm) is evident. b) Anomalies of the
656 NDVI from the mean trajectory of stable vegetation as a function of different forest types with
657 different species dominating (7 examples). The black line represents two standard deviations
658 from the mean.

659 Figure 9: a) NDVI time series for stable vegetation and for two areas (PSUs 108 and 68), which
660 were originally occupied by *C. glaucophylla*, *E. melanaphloia* and other *Eucalyptus* species (CP-
661 SLIEUS) and by *E. populnea* (PBX) respectively, but then cleared in 2000 and 2002. Trends in
662 the difference between the mean NDVI for all vegetation types combined and for the two
663 disturbed areas are shown for a) PSU 108 and b) PSU 68. The break points in the time series
664 indicate the clearing event and the magnitude of change in the NDVI, the confidence interval is
665 indicated in red.

666 Figure 10: Time series of the seasonal minimum of NDVI for a stable forest (PSU 67), a stable
667 non-forest (PSU 141) and the two different regrowth areas (PSU 68 and 108). Note that PSUs
668 141 and 68 were cleared of forest prior to 2000.

669 Figure 11: Comparison of estimated (BFAST breakpoint) intervals (blue) and reference clearing
670 intervals (cyan) for a) clearing and b) re-clearing. The breakpoint confidence intervals were
671 computed by BFAST, and the reference intervals were established with all available Landsat
672 imagery. The first date in the reference interval is plotted as base value (zero) on the y-axis. The
673 dashed red line shows a 40 day interval.

674 Figure 12: a) the clearing date determined using the BFAST breakpoint detection and b) the
675 magnitude of NDVI change at the time of clearing for all clearing and re-clearing areas within
676 the study region.

677