1 Phenology-Adaptive Pixel-Based Compositing using Optical 2 Earth Observation Imagery

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10 **Abstract:** The need for operational monitoring of landscape processes on the national to global scale led to an increased
11 demand for pixel-based composites using complete earth observation (EO) archives. Commonly, composites are generated
12 without explicit consideration of temporal criteria but are rather based on optimizing band indices within a pre-defined temporal
13 window. However, for certain applications phenology-adapted composites that represent the land surface as being in the same
14 phenological stage are required, e.g. tree type discrimination where greening up or senescence dates are modified by terrain
15 elevation. We developed a novel pixel-based compositing technique that dynamically adjusts the selection process to the
16 underlying land surface phenology (LSP) of each pixel. By doing so, phenologically sound composites across large areas can be
17 derived for regular intervals and different phenological points in time, e.g. peak, end or minimum of season. Various day-of-year
18 (DOY) scoring functions were implemented to flexibly define the phenological target. The technique is general enough for
19 global application and can be applied to any kind of gridded EO archive, herein demonstrated for MODIS and Landsat data.
20 Multi-annual composites were successfully generated for Zambia for most seasons. As an exception, we found even very
21 frequent MODIS observations to be insufficient for peak vegetation composites due to interference with the rainy season. The
22 phenology-adaptive composites were compared to static ones, i.e. using a single target DOY. Results clearly indicated that
23 biomass levels differ significantly between the techniques, and a phenological normalization across elevation gradients and land
24 cover classes could be achieved. However, the implications are non-trivial and the characteristics of both methods need to be
25 considered cautiously before deciding which approach is superior with regards to a specific thematic application. The quality of
26 the MODIS and Landsat composites, as well as the performance of the phenology-adaptive and static compositing techniques
27 were assured using a quantitative cross-comparison. A 12-year annual time series demonstrated the feasibility for land cover

change and modification mapping. Several change processes were clearly discriminable. The resulting phenologically coherent composites are important to establish national, regional or even global landscape monitoring, reporting and verification systems.

Keywords: Image processing, Landsat, large area monitoring, MODIS, phenological normalization, Zambia.

1. Introduction

The need for establishing operational landscape monitoring systems on the national to global scale is more pressing than ever (Hansen and Loveland 2012), e.g. to support the Reducing Emissions from Deforestation and Forest Degradation (REDD) mechanism. In this context, it is inevitable to establish national measurement, reporting and verification systems (Herold and Skutsch 2011), which can only be instated on the basis of non-leaking, wall-to-wall remote sensing products (DeFries et al. 2007; Gibbs et al. 2007).

The availability of moderate (100–500 m) to medium (10–100 m) resolution optical imagery steadily increased throughout the past decade, starting with Moderate Resolution Imaging Spectroradiometer data (MODIS, 250–500 m; Justice et al. 2002). Unlimited access to 30 m Landsat data (Woodcock et al. 2008) – recently complemented by 10–20 m Sentinel-2 data (Drusch et al. 2012) – fostered a new era in the field of earth observation (EO) and changed the usage of satellite imagery fundamentally (Wulder et al. 2012). However, with the ever increasing data volume also comes unprecedented data pressure: although data has become available to everyone, the high technical demand in terms of data handling currently bars part of the science community from utilizing complete EO archives adequately. As such, it is of major importance to provide ready-to-use, pre-processed baseline data for regular intervals. Pixel-based composites (PBC) are suitable products as they substantially reduce the data volume to enable ‘traditional’ analyses (e.g. land cover / change classification as in Griffiths et al. 2013a), provide cloud-free and seamless images over large areas (Holben 1986), but nonetheless make use of the full archive depth implicitly.

The generation of top-of-atmosphere (TOA) reflectance PBCs (e.g. Roy et al. 2010) is a straightforward and often sufficiently precise procedure. However, atmospheric correction is strictly necessary for multi-temporal analyses (Röder et al. 2005). For this purpose, a number of large-area production systems exist (e.g. Masek et al. 2006), which enabled the generation of seamless composites across the Carpathians (Griffiths et al. 2013b) and Canada (White et al. 2014). A full integration with further corrections for topographic and bi-directional effects, as well as homogenizing algorithmic for multiple sensors (e.g. Frantz et al. 2016a) might additionally enable within-state gradual change detection to the full extent – such as forest degradation (Vogelmann et al. in press).

Numerous compositing techniques were developed so far, and a detailed overview of existing methods and their specific (dis-) advantages can be found in Dennison et al. (2007) or Lück and van Niekerk (2016). Most commonly, compositing criteria are

58 based on optimizing band or index statistics(e.g. Flood 2013; Holben 1986), sometimes amended by view angle constraints(e.g.
59 Huete et al. 2002), in order to provide regularly spaced time series with fairly high frequency (e.g. Justice et al. 2002; Roy et al.
60 2010). Nevertheless, this approach is notfeasible whereadverse climatic settings and non-systematic acquisition plans prevent
61 gap-free annual coverage(e.g. Griffiths et al. 2013b).As such, another class of compositing algorithms not only uses observations
62 from a narrow temporal window, but instead considers all data within a couple of years. Instead of optimizing a single spectral
63 criterion, a parametric weighting scheme is used to combine a multitude of criteria, especially introducingtemporal
64 characteristicsto anchor the PBC to a pre-defined Day-of-the-Year (DOY, Griffiths et al. 2013b).

65 Shortcomings of this method mainly occur where phenological differences within target areas result in spectrally ambiguous
66 composites. For instance, barren fields might be falsely classified as fallows if the composited information was acquired in an
67 unfortunate phenological state (Griffiths et al. 2013a), or seasonal variations in broadleaved canopies might erroneously be
68 classified as deforestation (DeFries et al. 2007). This makes a strong case for the generation of phenologically coherent PBCs,
69 wherein spatial and temporal variations in LSP are consideredexplicitly. These can result fromlarge-scale factors like climate
70 (White et al. 1997), or can be effective at smaller spatial scales (e.g. due to local variations in water availability).Inter-annual
71 variations in LSP can also be substantial(White et al. 1997).

72

73 Consequently, a pixel-based LSP dataset as temporal target layer would allow for a more data-driven parameterization and
74 could eliminate the need to manually parameterize the target DOY. Accordingly, we propose a compositing technique, that

- 75 1) employs a parametric weighting scheme with full consideration of annual LSP at the pixel-scale, to generate phenologically
76 coherent composites across large areas,
- 77 2) allows for a data-driven parameterization of temporal compositing characteristics,
- 78 3) is flexible with regards of using different compositing criteria,
- 79 4) is general enough for global application, and
- 80 5) may be applied to any gridded EO archive.

81 We introduce our study area with an emphasis on LSP determinants in section 2. Section 3 provides a brief input data description
82 regarding reflectance and LSP products, including an assessment of data availability. The phenology-adaptive compositing
83 technique is described in section 4, and will be applied to MODIS and Landsat data. It is assessed whether the selected
84 observations are close to the target DOY and year. As a direct result of the outstanding temporal characteristics of MODIS, we
85 demonstrate the effectiveness of our approach by comparing phenology-adaptive MODIS PBCs to their“fixed-DOY” equivalents
86 using differences in the Enhanced Vegetation Index (EVI), followed by a quantitative analysis and a demonstration of the
87 phenological normalization across an elevation gradient and between land covers. Global applicability is demonstrated by

88 generating MODIS PBCs across a large latitudinal gradient. The Landsat PBC quality is ensured by a quantitative comparison to
89 MODIS, and eventually, a 12-year annual Landsat time series is employed to characterize drastic and decadal-scale scale
90 landscape dynamics. Results are presented in section 5, and are discussed in section 6, including a discussion of the utility of the
91 phenology-adaptive and static techniques with regard to different applications. The paper ends with conclusions in section 7.

92 **2. Study Area**

93 Zambia was chosen as primary study area (approx. $750 \times 10^3 \text{ km}^2$) due to its relevance as being qualified for REDD support.
94 Furthermore, the interaction of regional wind currents and terrain supported the development of distinct vegetation patterns with
95 both large-scale gradients and local variations in LSP.

96 Zambian climate is strongly dependent on elevation, and features tropical-warm climate on the predominant high plateaus
97 (1000 m a.s.l.). Tropical-hot climate characterizes the lower valley plains (325-920 m a.s.l.) in the South, while tropical-cool
98 climate is found on the highest plateaus, e.g. the Nyika Plateau in the North-East (2100-2200 m a.s.l.). The terrain of Zambia is
99 shown in Fig. 1a). The seasonality is closely tied to seasonal changes in large scale air movement and solar configuration, which
100 results in three hygrothermal seasons; i.e. (i) the hot wet season (November-April), (ii) cool dry season (May-August) and (iii)
101 hot dry season (September-October). The season start, end and lengths, and the precipitation sums are altered both by the local
102 relief and by the geographic location. In general, the season lengths and the precipitation sums decrease from North-West
103 (180-190 days, 1000-1400 mm) to South-East (120-130 days, < 800 mm) due to the temporally shorter influence of the
104 Intertropical Convergence Zone (ITCZ) in the South. The on- and offsets of the rains are also tied to the migration of the ITCZ
105 over Zambia, which is located north of Zambia during the dry season. On average, the rains start in mid-October in the North-
106 West and arrive in the South-East at the end of November. The rains stop in the South at mid-March and last until the end of
107 April in the North-West. The monthly rainfall sums for 2005 are shown in Fig. 1b). The timing of the minimum and maximum
108 temperatures also follow this pattern, where the coolest temperatures are found in June/July and the hottest temperatures in
109 October/November immediately before the onset of the rains (Schultz 1983).

110 The main part of the country is covered by semi-evergreen Miombo woodlands. Evergreen dry forests are found in western
111 Zambia on infertile Kalahari sands and are replaced by grasslands where seasonal waterlogging suppresses tree growth. The drier
112 and hotter southern part of the country is dominated by deciduous woodlands, where Mopane woodlands are found in the lowest
113 and driest regions. Permanent shallow flooding along the rivers and swamps, in combination with the relatively flat terrain support
114 large areas of seasonally flooded grasslands (Olson et al. 2001).

Fig. 1. Overview of the study area (Zambia). (a): Digital Elevation Model, acquired by the Shuttle Radar Topography Mission (SRTM). The Worldwide Reference System 2 (WRS-2) is superimposed. (b): Monthly rainfall sums for 2005, obtained from the Africa Rainfall Climatology version 2 (ARC2; Novella and Thiaw 2013).

3. Data

3.1. Surface Reflectance

1) MODIS

We acquired daily MODIS surface reflectance images (MOD09GA) with 500 m spatial and 1–2 day nominal temporal resolution (Vermote and Vermeulen 1999) from the Land Processes Distributed Active Archive Center's (LP DAAC) Data Pool. All images between 2003 and 2007 for the four tiles covering Zambia (as well as for 11 tiles covering a large latitudinal gradient) were downloaded, resulting in 1814 images per tile. The number of clear-sky observations is shown in Fig. 2 (a); on average 625 observations were available ($\sigma = 147$, $\min = 57$, $\max = 1013$). The reflectance data (blue: $0.469\mu\text{m}$, green: $0.555\mu\text{m}$, red: $0.645\mu\text{m}$, near infrared: $0.859\mu\text{m}$, shortwave infrared: $1.64\mu\text{m}$ and $2.13\mu\text{m}$) and view zenith angle layers were extracted, and the quality layers were parsed to compute the pixel distance to the next cloud or cloud shadow.

2) Landsat

We prepared a ready-to-use multi-sensor Landsat dataset, including reflectance and cloud detection products (Frantz et al. 2016a). All available Level 1T data from the Thematic Mapper (TM), Enhanced Thematic Mapper plus (ETM+), and the Operational Land Imager (OLI) were processed, and are stored in a gridded data structure in binary image format such that rapid pixel-based access to the full depth of the Landsat archive is instantaneously given. All images were available to the compositing algorithm, which was allowed to pick images as needed. Data from different sensors receive equal treatment in the proposed compositing approach. In this study, we focused on the period 2001–2012, where our data pool is populated with 60,800 and 131,601 gridded image datasets (see next paragraph) resulting from 1702 and 3825 original images in WRS-2 for the TM and ETM+, respectively.

138 A detailed description of the derivation of these inputs can be found in (Frantz et al. 2016a), and only a brief summary will be
 139 given here. NBAR products are generated using an integrated correction of atmospheric, topographic, bi-directional and adjacency
 140 effects. The atmospheric correction module was based on radiative transfer theory (Tanré et al. 1979) using a combined image-,
 141 database- and object-based estimation of aerosol optical depth. The MODIS precipitable water product (Gao and Kaufman
 142 2003) was used to characterize gaseous absorption. Topographic normalization was achieved with a modified image-based C-
 143 correction with 1-arc-Second SRTM data (USGS 2015). Bi-directional effects were reduced with a global set of MODIS-derived
 144 BRDF kernel parameters (Roy et al. 2016). The pixel distance to the next cloud or cloud shadow was computed with a modified
 145 version of the Fmask algorithm (Frantz et al. 2016a; Frantz et al. 2015; Zhu et al. 2015; Zhu and Woodcock 2012). The haze
 146 optimized transformation (HOT; Zhu and Woodcock 2012), and the view zenith angle were also appended to the output stack. All
 147 data were prepared in a regular grid (30 x 30 km), and share a single projection (Lambert Azimuthal Equal Area).
 148 The intersecting Landsat frames are superimposed in Fig. 1a); 49 WRS-2 frames were needed for full coverage. Due to the
 149 vicinity to the equator and the small swath of the Landsat sensors, overlaps between adjacent orbits are relatively small, which in
 150 combination with the relatively poor data availability poses challenges on generating seamless image products; Frantz et al.
 151 (2016b) showed that the average clear-sky revisit frequency in non-overlapping areas well exceeds 100 days in the wet season
 152 and is about 50 days in the dry season. The clear-sky data availability for the five-year period 2003–2007 is shown in Fig. 2 (b);
 153 on average 43.5 observations were available ($\sigma = 17.5$, min = 0, max = 161).
 154

155
 156 **Fig. 2.** Number of clear-sky observations for the MODIS (a) and Landsat (b) composites for the five-year period 2003–2007.

157 *3.2. Land Surface Phenology*

158 Zambian LSP is diverse, primarily as a function of elevation, climate and local variations in water availability. Since phenology
 159 on the southern Hemisphere is shifted compared to the northern Hemisphere, the vegetation maximum approximately coincides
 160 with the turn of the year. In order to facilitate computations, we do not strictly use DOY values, but use a continuous field of
 161 values in the algorithm internals, i.e. days since 01/01/0000. The average timing of three phenological key stages used throughout
 162 the manuscript is given in Table 1.

Table 1

Mean timing of three key stages of Land Surface Phenology (LSP) for 2005.

	Peak of season	End of season	Minimum of season
Abbreviation	POS	EOS	MOS
Mean DOY	25±	174±	245±
	January 25	June 23	September 2

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165 The peak of season (POS) is the timing of maximum vegetation growth and occurs during the rainy season. The minimum of
166 season (MOS) is the absolute minimum of vegetation development between two peaks and coincides with the hottest
167 temperatures in the dry season. The end of season (EOS) approximately coincides with the annual temperature minimum, where
168 drying already decreased the green stock substantially. The three parameters for 2005 are depicted in Fig. 3.

169 We prepared two sets of LSP data to guide the compositing process, one at moderate spatial resolution (250 m) and one at
170 medium spatial resolution (30 m). A detailed description of the derivation of these inputs can be found in (Frantz et al.
171 2016b), and only a brief summary will be given here. Moderate resolution LSP was obtained by applying the Spline analysis of
172 Time Series algorithm (SplITS, Mader 2012) to MODIS EVI time series (MOD13Q1/MYD13Q1). The day of composite
173 information was explicitly used to recreate the actually sensed time series, and the VI usefulness index (a sublayer given in the
174 MODIS products) was used for weighting the datapoints during the procedure. Data from both MODIS sensors on-board Aqua
175 and Terra were combined to increase the temporal resolution. Spline models were fit to the EVI time series and phenological
176 parameters were extracted thereof: POS and MOS are the timing of annual extremes, and the EOS is defined as the date where
177 the spline crosses 20% of the seasonal amplitude between POS and MOS. Following this, the spatial resolution was further
178 improved by fusing the moderate resolution LSP with the temporally limited Landsat reflectance (Frantz et al. 2016b). The fusion
179 intensively uses the information from the local pixel neighborhood at both resolutions, where a few discrete Landsat images are
180 used to disentangle the LSP with textural and spectral homogeneity metrics. The employed methods avoid the need of generating
181 a dense time series of synthetic Landsat-like images in a first step as the target layer is directly predicted at increased spatial
182 resolution.

183 The temporal LSP metrics were derived for the years 2001–2012. As an approximation, the average of the 12 year LSP is
184 computed by the compositing algorithm and is used for missing data, or for pre-2001 and post-2012 periods. The datasets were
185 generated with the same grid system as the MODIS and Landsat data, respectively, such that pixel-based operations can be used
186 during the compositing.

Fig. 3. Land Surface Phenology(LSP)for 2005; (a): peak of season (POS), (b): end of season (EOS), (c): minimum of season (MOS). (d): normalized histograms of POS, EOS and MOS (standardized by histogram maximum), and color bar for (a-c). The POS can be at the end or at the beginning of the calendar year, and as such, the data ranges from December 1, 2004 (DOY 336) to December 31, 2005 (DOY 365). The depicted color-ramp is used for all DOY images throughout the paper.

4. Methods

4.1. Compositing

Image compositing generally identifies the best suited observation in a given period of time on the basis of pre-defined criteria at the pixel-level. Following this definition, we consider each observation from the target year Y_t and from a number of bracketing years (i.e. $Y_t \pm y$), and use a parametric weighting scheme similar to Griffiths et al. (2013b) and White et al. (2014).

We determine the suitability of any observation by computing the total score S_T from a weighted linear combination of a number of thematic scores:

$$S_T = \sum WS / \sum W, \quad (1)$$

where the scores S characterize the phenology-adapted suitability of the acquisition day (S_D) and year (S_Y), the probability of cloudiness (S_C), the potential contamination with haze (S_H), the spectral correlation (S_R) and the view zenith angle (S_V), respectively. The scores are computed on a per-pixel basis and are defined to be within [0,1]. The employed transfer functions are described in the following sub-sections. The relative importance of the scores may be adjusted with the weighting parameters W ,

207 which are also in the range $[0,1]$, where $W = 0$ disables the usage of the corresponding score. The observation with the highest
 208 total score is selected for the composite. The mathematical symbols used throughout the paper are defined in Table 2.

Table 2

Definition of the mathematical symbols used in this paper.

Symbol	Meaning
Y_t, y	Target year and allowed number of bracketing years
D_t, D	Target Day-of-the-Year (DOY), DOY of image acquisition
$\Delta Y, \Delta D$	Absolute difference to target year and DOY
S_T	Total score
S_D, S_Y	Temporal scores for acquisition DOY and year
S_C, S_H, S_R, S_V	Auxiliary scores for cloud, haze, correlation and view angle
$W_D, W_Y, W_C,$ W_H, W_R, W_V	Weighting parameters for the temporal and auxiliary scores
p_0, p_1, p_2	Land Surface Phenology (LSP) metrics
s_0, s_1, s_2	Function values for the LSP metrics
σ_l, σ_r	Left- and right-tail width (sigma) for the Gaussian DOY scoring function
a, b	Shape parameters for the sigmoidal DOY scoring functions
Y_f	Y-factor; i.e. relative inter-/intra-annual contribution
d, d_{req}	Cloud and cloud shadow distance, and distance after the sky is assumed to be clear
$\theta, \theta_{\text{req}}$	View zenith angle, and angle at which S_V approaches 0

209

210 1) Intra-annual contribution: acquisition day

211 We use the pixel-based LSP to dynamically adjust scoring functions for each pixel. We use a sequence of three temporal LSP
 212 parameters, e.g.

- 213 • p_0 : POS,
- 214 • p_1 : EOS and
- 215 • p_2 : MOS.

216 Other sequences are also permitted, e.g. start of season (SOS), POS, EOS; which would simply result in composites anchored
 217 at a different phenological stage.

218 Thus, for each pixel and each year in $[Y_t - y, Y_t + y]$, there are three temporal parameters: p_0, p_1 and p_2 . The correct year of the
 219 LSP is selected by choosing the year in which p_1 is closest to the image under consideration, which is necessary if the
 220 phenological curve coincides with the turn of the year. Three function values (s_0, s_1 and s_2) need to be pre-defined, and they are to

be evaluated at p_0 , p_1 and p_2 for each pixel. The choice of s_0 , s_1 and s_2 triggers the usage of different scoring functions, i.e. either a Gaussian function or ascending/descending sigmoidal ones.

In the case of the Gaussian, s_0 , s_1 and s_2 must be in $[0,1]$ and $s_0 < s_1 > s_2$. A Gaussian function is then adapted to the LSP by numerically determining the width of the Gaussian bell σ ; the amplitude of the Gaussian is simply s_1 (typically $s_1 = 1$) and p_1 shall represent the target DOY. In order to adapt to asymmetric LSP, σ is determined for both tails separately:

$$\begin{aligned}\sigma_l &= [p_0 - p_1] / \sqrt{-2 \cdot \log(s_0/s_1)} \\ \sigma_r &= [p_2 - p_1] / \sqrt{-2 \cdot \log(s_2/s_1)}\end{aligned}\quad (2)$$

The DOY score S_D is computed with

$$S_D = \begin{cases} s_1 \cdot \exp(-0.5 \cdot [D - p_1]^2 / \sigma_l^2), & (D < p_1) \\ s_1 \cdot \exp(-0.5 \cdot [D - p_1]^2 / \sigma_r^2), & (D \geq p_1) \end{cases} \quad (3)$$

where the left-tail function is used if D is before p_1 . If not, the right-tail function is used.

The procedure of fitting a Gaussian to the LSP ($p_0 = \text{POS}$, $p_1 = \text{EOS}$, $p_2 = \text{MOS}$) is illustrated in Fig. 4 (a-d). In (a-b), s_0 , s_1 and s_2 are set to 0.01, 1.00 and 0.01; p_1 is assumed constant and p_0 and p_2 converge symmetrically towards p_1 (a) or progress forward asymmetrically (b). The Gaussian functions adapt to the changing LSP accordingly, which in practice would be the LSP of different pixels. In Fig. 4 (c-d), the LSP is held constant and the effect of modifying the function values is demonstrated; the Gaussians also adapt to these variations. The effect of increased s_0 and/or s_2 values on the composite would be that the chance of selecting a broader range of DOYs is increased. On the contrary, a more narrow Gaussian (i.e. low s_0 and/or s_2 values) would increase the selection rate of DOYs that are close to the target DOY.

To account for conditions where the selected DOY should not extend beyond or start before a certain date, we implemented descending and ascending sigmoidal functions, in which case p_0 or p_2 serve as target DOY layer. These functions are particularly useful if e.g., a ‘dry minimum’ composite should be created where only data from within the dry season are to be considered; the onset of the rains typically ends the season, triggers a green flush event, and thus alters the landscape quickly (see also Fig. 1 for the monthly rainfall sums).

$$S_D = \begin{cases} s_0 / (1 + \exp(a \cdot [D - p_1] + b)), & (s_0 > s_2) \\ s_2 / (1 + \exp(a \cdot [D - p_1] + b)), & (s_2 > s_0) \end{cases} \quad (4)$$

Analogous to the Gaussian type, function values s_0 , s_1 and s_2 at p_0 , p_1 and p_2 are pre-defined with

- $1 \geq s_0 > s_1 > s_2 \geq 0$ for a descending sigmoid or
- $0 \leq s_0 < s_1 < s_2 \leq 1$ for an ascending sigmoid.

The function parameters a and b are retrieved from Nelder-Mead Simplex Optimization (Nelder and Mead 1965) where the RMSE between s_0 , s_1 , s_2 and the evaluation of Eq. (4) at p_0 , p_1 and p_2 is minimized. s_0 or s_2 denote the function maxima and b causes the midpoint of the function to shift away from p_1 towards p_0 or p_2 . The steepness parameter a assumes positive (negative) values for the descending (ascending) type. Acquisition dates D that are before (after) D_t are scored with the LSP of the previous (next) year with the descending (ascending) sigmoid, such that they assume a very low S_D —in order to satisfy the need for the generation of within-season only composites.

The procedure of fitting the logistic S-curves is shown in Fig. 4 (e-h) for a descending (e-f) and an ascending case (g-h); $s_0 = 0.99$ (0.01), $s_1 = 0.10$ and $s_2 = 0.01$ (0.99). Fig. 4(e,g) demonstrate the capability of the sigmoid to adjust to the dynamic LSP, which in practice would be the LSP of different pixels. Analogous to the Gaussian type, the compositing behavior can be controlled by modifying s_0 , s_1 and s_2 where an increase generally increases the chance that DOYs further away from D_t are selected; exemplarily see Fig. 4 (f,h) for a sequence of s_1 values.

Fig. 4. Schematic illustration of the LSP-adaptive DOY scoring functions. The Gaussian type is shown in (a–d); the logistic S-curves in (e–h). For illustration purposes, we have either visualized fits to the variable LSP with constant function values (a, b, e, g), or have visualized fits to constant LSP but variable function values (c, d, f, h). The chosen LSP and scoring function values are indicated as p_{0-2} and s_{0-2} ; the point signatures indicate the p and s values, and ‘var.’ indicates that a parameter was varied; the variation of the p and s values can be taken from the x- and y-axis, respectively. For consistency with the following real-life examples, the p -values were tagged semantically with POS, EOS and MOS. In all cases, the target metric is the phenological parameter with the highest score, i.e. EOS (a–d), POS (e–f) and MOS (g–h).

Fig. 5. Illustration of the Y-factor Y_f for an arbitrary example. The figure shows isolines of the total score S_T , drawn with a dependence on ΔY and ΔD . The right tail Gaussian type was chosen and two years around the target year are allowed; i.e. $y = 2$. The total score was computed as a combination of the Year score S_Y and the DOY. The higher Y_f , the higher is S_Y – and the smaller is the influence of ΔY on S_T .

2) Inter-annual contribution: acquisition year

In the case of generating composites from multi-annual observations, it is required to define tradeoff criteria between data from Y_t and acquisitions from other years that potentially are closer to D_t . Preferably, observations from Y_t should be selected to minimize the risk of land cover change between the years while acquisitions close to D_t are needed to increase the phenological consistency. Observations from bracketing years should not be used until the data availability in Y_t is too limited. As these are contradicting demands, we introduce the Y-factor Y_f , which defines the tradeoff between inter- and intra-annual data contribution with a single parameter. To adapt to spatial variations in the steepness of vegetation development or senescence, Y_f is parameterized with a dynamic adjustment on the basis of pixel-based LSP. Recall that the intra-annual scoring is determined from p_0 , p_1 and p_2 using different scoring functions. We slice the interval of the most dynamic range of p_0 , p_1 , p_2 into intervals $p_{\leftrightarrow}$ that are defined by Y_f and the allowed number of bracketing years y :

$$p_{\leftrightarrow} = \begin{cases} (p_1 - p_0) / ([y + 1] \cdot Y_f), & (D < p_1) | (s_0 > s_2) \\ (p_2 - p_1) / ([y + 1] \cdot Y_f), & (D \geq p_1) | (s_2 > s_0) \end{cases} \quad (5)$$

where the first equation is used for the left-tail Gaussian or the descending sigmoid, and the second equation for the right-tail Gaussian or the ascending sigmoid.

296

297 The Year score S_Y is defined to enable a merely DOY-driven selection, but with a penalty on the bracketing years. It is the
 298 evaluation of the DOY scoring function relative to the function maximum at $\Delta Y \cdot p_{\leftrightarrow}$ for the Gaussian type

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300

$$S_Y = \begin{cases} s_1 \cdot \exp(-0.5 \cdot [\Delta Y p_{\leftrightarrow}]^2 / \sigma_1^2), & (D < p_1) \\ s_1 \cdot \exp(-0.5 \cdot [\Delta Y p_{\leftrightarrow}]^2 / \sigma_1^2), & (D \geq p_1) \end{cases} \quad (6)$$

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302 and the sigmoidal types

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$$S_Y = \begin{cases} s_0 / (1 + \exp(a[p_0 + \Delta Y p_{\leftrightarrow} - p_1] + b)), & (s_0 > s_2) \\ s_2 / (1 + \exp(a[p_3 - \Delta Y p_{\leftrightarrow} - p_1] + b)), & (s_2 > s_0) \end{cases}, \quad (7)$$

305

306 Fig. 5 illustrates the influence of Y_f on S_T for an arbitrary example where D is after p_1 , and the DOYs are scored with the right-
 307 tail Gaussian with $s_1 = 1$ and $s_2 = 0.01$; $y = 2$ years. The total score S_T was computed using S_D and S_Y only. Three different Y_f are
 308 shown in (a-c) which alter the curvature of the S_T isolines. In the case of $Y_f = 3$, the isolines are rather vertical, which means that
 309 S_T for a given ΔD do not differ substantially between the years, and observations from the bracketing years may be included in
 310 the composite. In the case of $Y_f = 0.75$, the isolines are curved substantially, which strongly decreases the selecting rate of non- Y_f
 311 observations. As an example (green isoline), observations with $\Delta D \leq 23$ and $\Delta Y = 1$ can only be selected if there is no
 312 observation in $\Delta Y = 0$ with $\Delta D \leq 61$. The chance of selecting a $\Delta Y = 2$ observation is even worse, as the same S_T cannot be
 313 achieved.

314

315

316 3) Cloud distance score

317 We score the pixel's distance to the next cloud or cloud shadow d with a sigmoid in order to devalue pixels that are in close
 318 proximity to a cloud or a cloud shadow. Fmask cloud detections are generally of high quality (Zhu and Woodcock 2012) but they
 319 are not perfect (Frantz et al. 2015; Zhu and Woodcock 2014), thus cloud remnants remain in the data and especially shadows
 320 might be missed. Nevertheless, clouds are typically clustered and unidentified shadows are also constrained to the proximity of
 321 the more reliably detectable clouds. Therefore, the concentric devaluation of pixels around the detected clouds also accounts for
 322 the missed objects. Griffiths et al. (2013b) defined a parameter d_{req} beyond which the sky is assumed to be clear. We slightly
 323 modified the cloud scoring function (Fig. 6, red) to adapt better to different d_{req} :

324

$$S_C = 1 / (1 + \exp(-10/d_{\text{req}} \cdot [d - d_{\text{req}}/2])) \quad (8)$$

Fig. 6. Cloud distance and haze scoring functions; d_{req} was set to 100 pixels.

4) Haze score

The utilized pre-processing framework included a full radiometric treatment of the data (Frantz et al. 2016a). Nevertheless, local plumes of thick haze are still present in the imagery and are also subject of omission in Fmask, e.g. haze caused by biomass burning is not detected reliably due to its transparency and warmth. Therefore, we added the Fmask Haze Optimized Transformation (HOT; Zhang et al. 2002; Zhu and Woodcock 2012) to the output stack in the pre-processing framework. The HOT has already proven its usability in compositing techniques (Lück and van Niekerk 2016), and as such, we use this proxy for devaluating hazy observations with a sigmoid (see Fig. 6, dashed):

$$S_H = 1 / (1 + \exp(10/0.02 \cdot [HOT + 0.015])). \quad (9)$$

5) Correlation score

EO imagery can contain a variety of errors or undesired effects which are hard to account for with scoring functions tailored for a specific purpose. This especially applies if apriori knowledge about potential error sources is not available, and/or specific avoidance strategies cannot be developed. Undesired effects may be data artifacts (e.g. due to impulse noise or any other sensor anomaly see Fig. 7a), residual misregistration, or undesired transient phenomena like short-term flooding, active fires or missed clouds/shadows.

As such, we developed a general criterion, which relates a given spectrum to the pixel's spectral stability, and thus minimizes outlier-induced noise regardless of the type of noise. Through time, spectra (with n_b bands b) are commonly highly correlated, and as such, we compute the correlation between the given observation o and all other observations o_i (n = number of observations within $Y_t \pm y$):

$$r_{oo_i} = \frac{\sum_b^{n_b} (\rho_{o,b} - \bar{\rho}_o)(\rho_{o_i,b} - \bar{\rho}_{o_i})}{\sqrt{\sum_b^{n_b} (\rho_{o,b} - \bar{\rho}_o)^2 \sum_b^{n_b} (\rho_{o_i,b} - \bar{\rho}_{o_i})^2}}. \quad (10)$$

The mean absolute correlation(Fig. 7a) is computed with

$$r_\mu = \frac{1}{n} \sum_i^n |r_{oo_i}|, \quad (11)$$

then used as spectral stability proxy in the computation of the correlation score (Fig. 7b):

$$S_R = 1 / (1 + \exp(-10 / (0.5 \cdot 2/3) \cdot [r_\mu - 0.5 \cdot 4/3])). \quad (12)$$

Fig. 7. Exemplary illustration of the spectral stability assessment and correlation scoring function. (a): mean absolute correlation derived from all spectra within the compositing period, and Landsat-7 NIR image (Path/Row 172/072) affected by sensor anomalies. (b): correlation scoring function.

6) View angle score

Wide swath sensors like MODIS provide near-daily global coverage, though off-nadir data is of poorer quality due to the “bowtie” effect, where the FOV at the scan edge (approx. 65°) is approximately 2.0 and 4.8 times larger than at nadir in the track

and scan directions, respectively (Wolfe et al. 1998). It is well known that the consideration of view angle effects improves composite quality considerably (e.g. Chuvieco et al. 2005), therefore we use a sigmoid to devalue off-nadir pixels on the basis of the view zenith angle θ of a given observation (see Fig. 8):

$$S_V = 1 / (1 + \exp(10 / \theta_{\text{req}} \cdot [\theta - \theta_{\text{req}} / 2])). \quad (13)$$

θ_{req} is the angle at which S_V approaches 0, and can be adapted with respect to the viewing geometry of a specific sensor.

Fig. 8. View zenith angle scoring function; θ_{req} was set to 40° and 7.5° for MODIS and Landsat, respectively.

4.2. Implementation and user interaction

The code is entirely based on open-source software and is written in C. The GNU Scientific Library is used for optimization procedures. Shared memory parallelization was implemented by utilizing the Open Multi-Processing (OpenMP) API. The compositing algorithm works on a per-tile-basis, though data from the requested tiles are directly written to a single output file, which is basically a mosaic of composites.

If required, the compositing algorithm can be parameterized by setting only a few parameters. The spatial extent, the target Year Y_t , the number of bracketing years y and the Y-factor Y_f must be set. If the phenology-adaptive approach is to be used, the user must input the LSP data (p_0 , p_1 and p_2) and needs to define the corresponding function values s_0 , s_1 and s_2 . If static composites are to be created, fixed values for p_0 , p_1 and p_2 need to be defined instead. The function type (Gaussian or sigmoid) is automatically chosen from the given s values. The weighting parameters W can also be modified and individual scores S can be disabled. Several output files can be generated on demand:

- **pixel-based composites** are written by default,
- **composite information** about (i) the number of considered clear-sky observations (in dependency of d_{req} – see Fig. 2), (ii) the selected D , (iii) ΔD , (iv) ΔY , (v) sensor ID (4, 5, 7 or 8 in the case of Landsat), (vi) Path/Row of the best observation, and (vii) the 12-year variability of LSP,

- **scores** of the best observation ($S_T, S_D, S_Y, S_C, S_H, S_R, S_V$), and
- **spectral variability metrics** can be produced optionally. The spectral variability is a representation of the stability or variation of the land surface during the $2y+1$ year compositing period. Spectral variability metrics were shown to be an asset in land cover classifications (Griffiths et al. 2013b). Each clear-sky observation which is sufficiently far away from the next cloud (in dependency of d_{req}) contributes to these metrics. Mean (i), standard deviation (ii), minimum (iii), maximum (iv), range (v), skewness (vi) and kurtosis (vii) may be output.

4.3. Application to EO archives

We demonstrate our method with MODIS and Landsat archives. Very dense MODIS data(temporal resolution ~ 2 days) enable the selection of observations which are as close as possible to the target DOY, and are thus optimal to demonstrate the temporal aspects of the presented approach. In order to demonstrate the effect of using pixel-based LSP, we generated a set of phenology-adaptive PBCs (using the coarse resolution LSP) and a set using a static target DOY, i.e. the mean value of the LSP (see Table 1). For each set, three seasonal composites for 2005 ± 2 were generated: POS, EOS and MOS. The seasonal PBCs were generated using the same input LSP layers, but with different DOY scoring functions, i.e. the descending sigmoid, two-tailed Gaussian and ascending sigmoid, respectively. The EVI was computed for each composite as benchmark for differences in vegetation development as a result of the two compositing techniques. Differences between the techniques are shown and the PBCs are compared quantitatively. The mean error (ME) as a measure for bias, the mean absolute error (MAE), the root mean squared error (RMSE) and the coefficient of determination (R^2) were computed for each combination. Spatial autocorrelation was reduced with a random selection of $\sim 17,500$ samples using Poisson Disc sampling (Tulleken 2008). As additional proof of concept, we examine the (non-)relationship between EVI and elevation for a small subset with a large elevation gradient and a number of land cover classes for both the phenology-adaptive and the static PBCs. A fairly low Y-factor was chosen to give precedence to target-year observations. The full parameterization is summarized in Table 3. W_D and W_Y were set to 1. W_H was set to 0, because the HOT was not available as we acquired atmospherically corrected MODIS data. W_C was set to 0, because we did not encounter severe data artifacts in the resulting composites, and the correlation score is computationally expensive for a very large number of input images (1814 images), thus we considered the cost-benefit ratio ineffective for its usage with dense MODIS data. W_C and W_V were set to 0.33, in order to guarantee that S_D cannot be overruled by close-nadir and cloud-free observations in unfavorable seasons. The potential for global applicability is demonstrated by generating MODIS EOS PBCs for a large latitudinal gradient from boreal Russia to South Africa. We generated a phenology-adaptive version, and static PBCs that were anchored at the hemispheric mean EOS, which is DOY 256 and 106 for the Northern and Southern Hemisphere, respectively.

Table 3
Parameterization of the MODIS and Landsat composites.

set	peak of season	end of season	min. of season	peak of season	end of season	min. of season
	MODIS	MODIS	MODIS	Landsat	Landsat	Landsat
Y_t, y	2005 $\pm$ 2	2005 $\pm$ 2	2005 $\pm$ 2	2005 $\pm$ 2	2005 $\pm$ 2	2005 $\pm$ 2
Y_f	0.75	0.75	0.75	0.75	0.75	0.75
p_0, p_1, p_2	LSP	POS, EOS, MOS	POS, EOS, MOS	POS, EOS, MOS	POS, EOS, MOS	POS, EOS, MOS
	static	25, 174, 245	25, 174, 245	25, 174, 245	25, 174, 245	25, 174, 245
s_0, s_1, s_2	0.99, 0.1, 0.01	0.01, 1, 0.01	0.01, 0.1, 0.99	0.99, 0.1, 0.01	0.01, 1, 0.01	0.01, 0.1, 0.99
scoring function	descending	two-tailed	ascending	descending	two-tailed	ascending
	sigmoid	Gaussian	sigmoid	sigmoid	Gaussian	sigmoid
$W_D, W_Y, W_C,$	1.00, 1.00, 0.33,	1.00, 1.00, 0.33,	1.00, 1.00, 0.33,	1.00, 1.00, 0.20,	1.00, 1.00, 0.20,	1.00, 1.00, 0.20,
W_H, W_R, W_V	0.00,0.00, 0.33	0.00,0.00, 0.33	0.00,0.00, 0.33	0.20, 0.20, 0.33	0.20, 0.20, 0.33	0.20, 0.20, 0.33
d_{req}, θ_{req}	10, 40	10, 40	10, 40	100, 7.5	100, 7.5	100, 7.5

424

425 In the next step, we applied both the phenology-adaptive and static compositing techniques to the Landsat data, using the
426 medium resolution phenology or the mean LSP values. Analogously to MODIS, we generated three seasonal PBCs for 2005 $\pm$ 2
427 years, i.e. POS, EOS and MOS. The Landsat PBCs were cross-compared with MODIS to ensure data quality. To lessen the effect
428 of differing spatial resolution, the Landsat PBCs were degraded to 500 m using a MODIS point spread function (Barnes et al.
429 1998). The sampling procedure and statistical measures are the same as described in the last paragraph and are presented together
430 with the cross-comparison between the MODIS PBCs. The complete parameterization is summarized in Table 3. We used all
431 scores, while ensuring that the auxiliary scores cannot outmax the temporal ones. In order to show the potential for land cover
432 change mapping, we generated an annual Landsat EOS time series (2001–2012 $\pm$ 0) with the phenology-adaptive technique. The
433 Change, Aftereffect and Trend (CAT, Hird et al. 2016) transform was applied to the EVI representations for visualizing both
434 drastic and gradual landscape dynamics across whole Zambia at medium resolution. Due to the non-optimal data availability of
435 Landsat data, we rigorously rejected all observations that deviate more than $\pm$ 16 days from D_t .

436

437

438

5. Results

5.1. MODIS composites

We generated phenology-adaptive MODIS composites centered at the POS, EOS and MOS, as well as static PBCs that only use the mean LSP values. The same LSP metrics were chosen for each PBC while only altering the scoring values s_0 , s_1 and s_2 , thus triggering the use of the descending sigmoid, two-tailed Gaussian and ascending sigmoid functions. We used a fairly low Y -factor to prefer data from Y_t if available. We uploaded the generated MODIS composites to the Mendeley Data Repository (<https://data.mendeley.com/datasets/bj7jn39ds2/draft?a=e0e0a086-f665-40f1-86d2-9f20c292f9a6>).

Fig. 9 depicts the PBCs for the three seasons (rows). The phenology-adaptive (static) PBCs are shown in the first (second) column. The third column depicts the difference in EVI; red colors indicate a higher EVI in the phenology-adaptive images. The selected DOY, ΔD and ΔY are shown in Fig. 10. Basic statistics are summarized in Table 4. The number of observations is identical for all composites because they were generated with the same input data (see Fig. 2 (a)).

Based on visual inspection, the POS PBCs are of least quality and are characterized by a stained appeal. The EOS and MOS PBCs are of highest quality. Bi-directional effects are readily visible in the static MOS PBC as there is a distinct discontinuity between neighboring orbits, and to a smaller degree also in the static EOS PBC. The swaths are not visible in the phenology-adaptive versions, although generally more grained, which is a side effect of the phenology-adaptive approach in that the extensive mixing of acquisition dates on the pixel scale increases the angular variability, and thus masks the visibility of bi-directional effects on the orbital scale. However it needs to be stated that bi-directional effects are still present on the pixel scale.

The EOS(MOS) composites differ by less than ± 7 (± 10) days from D_t . On the contrary, the POS PBC differs by more than a month (and have a large standard deviation), despite a stronger contribution of the bracketing years. Virtually all data of the EOS PBC were acquired in Y_t , whereas the POS and MOS PBCs also include data from $\Delta Y \geq 1$, which in both cases is more pronounced in the phenology-adaptive version. The selected DOYs resemble the LSP input patterns presented in Fig. 3 (with exception of the POS PBC), whereas the static versions show little spatial variation besides the acquisition orbits.

Almost all parts of the EOS PBCs differ substantially with both positive and negative EVI differences. Different ecosystems and topographic units are clearly discriminable in the ΔEVI image. Differences in the POS images are rather regionalized and coincide with the previously described stained patterns. The MOS PBCs are characterized by only small negative ΔEVI values, while larger parts of Zambia have high positive ΔEVI values.

Fig. 9. MODIS PBCs for 2005±2 for POS(a-c), EOS(d-f) and MOS(g-i). Phenology-adaptive and static composites are shown in the first (a,d,g) and second (b,e,h) column, respectively. The depicted band combination is RGB = near infrared, shortwave infrared and red, thus combining complementary information from the three different wavelength domains. The band combination, as well as the same stretch is applied to all reflectance composites throughout the paper. EVI differences between the phenology-adaptive and static composites are shown in the third column (c,f,i); red colors indicate more biomass in the phenology-adaptive composite. The green rectangle in (f) indicates the extent of Fig. 11.

Fig. 10. Temporal characteristics of the composites in Fig. 9. POS (a-b), EOS (c-d), and MOS (e-f) are shown in the rows. The left half of the figure (a,c,e) refers to the phenology-adaptive composites; the right half (b,d,f) to the static composites. For each composite, the selected DOY, the difference to the target DOY ΔD and the difference to the target year ΔY are shown. The same color ramps are applied throughout the paper where appropriate.

Table 4

Temporal basic statistics for the generated MODIS and Landsat composites.

			ΔD		ΔY		ΔD		ΔY	
			MODIS		MODIS		Landsat		Landsat	
Y _f			μ	σ	μ	σ	μ	σ	μ	σ
D _t = POS	LSP	0.75	42.41	27.90	0.24	0.43	50.31	28.68	0.30	0.46
D _t = 25	static	0.75	34.57	19.26	0.11	0.32	44.48	24.79	0.17	0.38
D _t = EOS	LSP	0.75	5.57	5.98	0.00	0.05	16.80	17.21	0.02	0.15
D _t = 174	static	0.75	6.43	5.19	0.00	0.01	16.28	11.17	0.02	0.14
D _t = MOS	LSP	0.75	9.87	10.66	0.21	0.41	16.27	14.13	0.59	0.50
D _t = 245	static	0.75	8.78	5.62	0.03	0.16	15.57	9.74	0.65	0.47

Fig. 11 displays the MODIS EOS EVI layer for a subset with a large elevation gradient. The phenology-adaptive version is shown in the left column and the static one in the right column. The phenology-adaptive PBC (a) is spatially homogeneous, whereas larger differences can be seen in the static PBC (b). As can be seen in (d), the EVI increases with elevation, whereas this

elevation-dependency is largely normalized in (c). There is also land cover dependent variability (f), and as can be seen in (e), the phenological normalization removes large parts of the within and between ecoregion differences.

Fig. 11. EVI of the MODIS EOSPBCs for a sample area (see Fig. 9) with a large terrain elevation gradient (> 1000 m). The phenology-adaptive version is shown in the left column; the static version in the right column. (a–b): EVI maps; the brown–green color ramp is linearly stretched from 0–0.5, (c–d): 2D-histograms between EVI and terrain elevation, (e–f): EVI boxplots for the World Wildlife Fund terrestrial ecoregions (Olson et al. 2001); A–D are Central Zambebian Miombo woodlands, Southern Miombo woodlands, Zambebian and Mopane woodlands and Zambebian flooded grasslands, respectively.

5.2. Global application

Global applicability is demonstrated with MODIS EOS PBCs (2005) for a large latitudinal gradient from boreal Russia to South Africa (Fig. 12). We generated a phenology-adaptive version (b), and static PBCs that were anchored at the hemispheric mean EOS, which is DOY 256 and 106 for the northern (a) and southern hemisphere (c), respectively. The tropics are similar in all PBCs. Large differences are visible in the sub-tropical belts (~10°N–10°S), where the phenology-adaptive version has produced the greatest homogeneity between the North and South. The static northern PBC has higher (lower) biomass in the North (South), whereas the static southern PBC has lower and approx. equal biomass in the North and South, respectively. Southern Africa is also different, where large parts of the sub-continent look barely vegetated in (a). Similarly, snow is very

498 abundant at mid- and high northern latitude in (c). The phenology-adaptive version is also not free of snow but the northern
 499 temperate and boreal forest is spatially more homogeneous in terms of biomass than in the northern static PBC.

500
 501 **Fig. 12.** MODIS PBCs for the target year 2005 across a large latitudinal gradient. The composites are EOS variants, where (b) is a phenology-adaptive
 502 composite; (a) and (c) are static composites that were anchored at the average EOS of the Northern (a) and Southern Hemisphere (c). The depicted band
 503 combination is RGB = near infrared, shortwave infrared and red.

505 5.3. Landsat composites

506 Analogously to MODIS, phenology-adaptive and static Landsat PBCs were generated for the POS, EOS and MOS with
 507 descending sigmoid, Gaussian and ascending sigmoid functions, respectively. Fig. 13 depicts the phenology-adaptive PBCs. The
 508 selected DOY, ΔD and ΔY are shown below the composites. Basic statistics are summarized in Table 4. The number of
 509 observations is identical because they were generated with the same input data (see Fig. 2 (b)).

510 The Landsat PBCs look similar to the MODIS ones, and analogously, the POS PBC is of least quality, while the EOS and MOS
 511 PBCs are of high visual quality.

512 The EOS and MOS composites differ by less than ± 17 days from D_t , while the POS PBC differs by more than ± 50 days (and
 513 have a large standard deviation). The standard deviation of the MOS PBC is slightly lower than in the EOS, which is due to non-
 514 optimal data availability in some orbits in the EOS case. The MOS PBC has a higher share of data from the bracketing years,
 515 which in this case alleviated the non-optimal data availability in Y_t . Overall, the temporal differences are larger than in the
 516 MODIS PBCs because of the smaller temporal resolution. In case of the EOS and MOS PBCs, the selected DOYs resemble the
 517 LSP input patterns presented in Fig. 1, although not as precisely as the MODIS PBCs.

518 **Fig. 13.** Phenology-adaptive Landsat PBCs for 2005±2 for POS (a-c), EOS (d-f) and MOS (g-i). For each composite, the selected DOY, the difference to the target
 519 DOY ΔD and the difference to the target year ΔY are shown.

521

522

523 5.4. *Cross-comparison*

524 The quantitative cross-comparison of the phenology adaptive and static versions of the MODIS and Landsat PBCsis shown in
525 Fig. 14 with seasons and derived statistical measures in the rows and columns, respectively. Green colors indicate a good match,
526 red colors indicate differences.

527 The within-sensor POS PBCs have low ME, low MAE and RMSE and high R^2 . The within-technique POS PBCs have high
528 ME, high MAE and RMSE and yet high R^2 . The between-sensor-and-technique PBCs have similar errors as the within-technique
529 composites

530 The within-sensor EOS PBCs have low ME, fairly high MAE and RMSE and intermediate R^2 . The within-technique EOS
531 PBCs have high ME, relatively low MAE and RMSE and relatively high R^2 (compared to within-sensor EOS). The static
532 MODIS and Landsat PBCs have highest R^2 . The between-sensor-and-technique PBCs have the highest errors.

533 The within-sensor MOS PBCs have high ME with higher EVI in the static composites. The within-Landsat PBCs are
534 characterized by low MAE and RMSE and high R^2 , whereas the within-MODIS PBCs have good to intermediate MAE, ME and
535 R^2 . The within-technique MOS PBCs have low ME, RMSE and good R^2 values. The agreement in MAE, RMSE and R^2 is partly
536 better and partly worse in the within-sensor and within-technique PBCs .The between-sensor-and-technique PBCs have the
537 highest errors.

538

Fig. 14. EVI cross-comparison of the MODIS and Landsat PBCs for POS (a–d), EOS (e–h) and MOS (i–l). Statistical measures are shown in the columns with mean error (ME), mean absolute error (MAE), root mean squared error (RMSE) and coefficient of determination (R^2) from left to right. The MODIS/Landsat PBCs are abbreviated with ‘MOD’/‘LND’ and the phenology adaptive and static versions with ‘LSP’/‘STA’, respectively. The residuals are calculated as $e = x - y$; e.g. the lower-left ME value in (a) means that the static MODIS composite features higher EVI values than the phenology adaptive Landsat composite. The color ramps are consistent within each column.

5.5. Time series application

Fig. 15 depicts the CAT transformation applied to the annual Landsat EOS PBC time series. The CAT transformation was developed to capture change events and gradual decadal-scale landscape dynamics and is effective to ‘distill’ the complete data archive into three variables that describe very different aspects of a changing landscape (Hird et al. 2016). The Change (largest difference between years), Aftereffect (mean of post-change) and Trend (slope of regression of the entire time series) components are mapped to RGB space and can be directly interpreted. Deforestation appears in red–orange colors; pure red colors indicate a stand-replacing disturbance, whereas orange colors indicate some post-change biomass which represents a typical agricultural temporal signature. Stable forests appear in green (high biomass, no change or trend), forest degradation in yellowish tones (negative trend; the mixture of red and green depends on the standing biomass and the rate of change), gradual

554 regrowth in cyan (no change, gradual increase of biomass) and pinkish colors denote areas where a change and a positive trend
 555 were detected; these are mainly land covers that are characterized by strong inter-annual variations of biomass like the flooding
 556 plains and swamps. The CAT transformation is shown for complete Zambia, and for three subsets that depict different change
 557 processes. Forest degradation is depicted in Fig. 15 (b-d), where the yellowish areas represent areas where trees were selectively
 558 removed, while an increase in biomass is evident in the enclosed forest patch. Deforestation is readily visible in (e-g), where
 559 large forest areas were cleared to establish mechanized agriculture, leaving only isolated pockets of intact forest. A savanna-
 560 mosaic landscape is depicted in (h-j), where most part of the area was burnt before our analysis period. The area is largely
 561 characterized by an increase in biomass (blue areas), whereas the previously unburnt woodlands are stable. The flood plains are
 562 characterized by a high change, which rather is an effect of inter-annual variability within this land cover.

564 **Fig. 15.** CAT Transformation of the annual EOS Landsat PBCs, mapped to RGB space as Change, Aftereffect, and Trend, respectively. Three exemplary subsets
565 (100 km²) depicting different change processes are shown in (b–d; 13.02°S / 30.76°E), (e–g; 14.78°S / 27.21°E), and (h–j; 16.23°S / 25.79°E) with CAT
566 transformation, 2002 and 2012 composites from left to right.

567 **6. Discussion**

568 *6.1. MODIS composites and selected seasons*

569 We developed and implemented a compositing technique based on a parametric weighting scheme as firstly proposed for
570 Landsat data by Griffiths et al. (2013b). Besides implementing new selection scores and enabling the code to be applied to
571 optical EO imagery in general, we especially introduced a novel methodology for incorporating phenological information in the
572 compositing process. As the Landsat data availability is relatively poor in this part of the world, the temporal compositing
573 capabilities were tested with the daily MODIS product and were compared to a static equivalent, i.e. fixed DOY representing the
574 mean state of the LSP. These static PBCs are comparable to the Griffiths method. Multi-annual PBCs were generated for the peak
575 of season, end of season and minimum of season. We used three different scoring functions (descending sigmoid, two-tailed
576 Gaussian and ascending sigmoid), which resulted in three very different composites, although the same input data were used.
577 The algorithm successfully generated seasonal PBCs as close as possible to the phenological/static targets. In case of the
578 phenology-adaptive version, the selected DOYs closely resemble the LSP input. The three seasons were chosen as they
579 potentially enable different analyses. Dry season images (e.g. EOS) are often employed for forestry applications due to the
580 improved separability between trees and grass (Armston et al. 2009). The driest point in time (i.e. MOS) is not necessarily suited
581 to accomplish this task as deciduous trees can lose their foliage completely. This time may be appropriate for mapping burned
582 areas. Even though the generation of POS PBCs is problematic in areas where the rainy season and vegetation growth coincide,
583 POS PBCs may be highly suitable for certain applications like the derivation of peak biomass. Often a combination of different
584 seasons might be the best choice to accomplish specific tasks, e.g. to differentiate between woody and herbaceous biomass in
585 EOS, and to quantify annual biomass in POS PBCs, respectively. Other DOY-based LSP parameters can easily be input, e.g.
586 start of season or inflection point parameters that might provide further essential information on ecosystems.

587 *6.2. Landsat composites*

588 Analogously to MODIS, multi-seasonal Landsat PBCs were generated. The selected DOYs resemble the LSP input fairly well.
589 Similar to MODIS, the POS was of insufficient quality, whereas the EOS and MOS PBCs are visually homogenous and are
590 characterized by relatively low differences to the target. However, the differences are larger than in the MODIS PBCs, which we
591 attribute to the lower temporal resolution. The revisit frequency of MODIS was 1–2 days, whereas the nominal Landsat revisit
592 time is 8–16 days in SLC-on and off image areas, respectively. In practice, this frequency cannot be met, see e.g. (Frantz et al.

2016b). The visibility of the acquisition orbits in the DOY and PBC images is also a result of the worse temporal coverage. However it is noted that this applies to any compositing technique.

6.3. Phenology-adaptive vs. static composites

1) Regional application

Despite the visual congruence of the phenology-adaptive and static Zambian composites, there are in fact substantial differences that are illustrated in the ΔEVI images (Fig. 9). By definition, the phenology-adaptive versions should have higher (lower) EVI values than the static POS (MOS) PBCs due to the employed one-sided sigmoidal scoring functions. Areas, where the LSP matches the Zambian average should have comparable EVI values. On the contrary, the phenology-adaptive EOS PBC should have approximately equal amounts of pixels with higher and lower EVI values as a two-tailed Gaussian function was used.

The POS results are hard to interpret, since the target DOY could not be approached successfully as a consequence of persistent cloud coverage in the rainy season. This can be readily seen in the composites as reflectance discontinuities. The quantitative cross-comparison further supports this: The within-MODIS PBCs have low ME and MAE values in EVI, thus the PBCs are very similar. This does not imply that the POS PBCs are of high quality. On the contrary, the PBCs are simply similar as both versions are rather bound by the end of the rains (in fact, 60% of the pixels are the same observations). This also applies to the Landsat PBCs, which are even more similar as the temporal resolution is even more problematic (~70%).

On the contrary, The EOS and MOS PBCs were of high quality and the target DOY could be approached with high precision. The EOS PBCs feature large connected areas with both negative and positive EVI differences, where the EOS occurs earlier/later than the Zambian average. The quantitative assessment supports this. The within-sensor PBCs have low ME, thus there is no bias which is a result of the two-sided Gaussian scoring function that caused both negative and positive EVI differences. MAE, RMSE are high and R^2 are intermediate, which means that there are indeed larger differences pointing to a successful levelling of phenological differences.

The MOS PBCs features large patches of positive differences, as the phenology-adaptive approach has selected observations close to the seasonal minimum. There are also some negative differences, although the magnitude and abundance is not as large as that of the positive ones, and they do not form large connected areas. Potential error sources may be attributed to minor noise in MOD09GA data or to the derivation of LSP itself. Nevertheless, the compositing produced the desired results at large, which is also backed by the quantitative cross-comparison as there is a large positive bias (ME) between the within-sensor PBCs due to the one-sided sigmoid. MAE is relatively low, which is due to the fact that the static PBC was parameterized with the mean value of the phenology used in the phenology-adaptive version, and as such, only the land covers that deviate from this mean are different.

623 2) *Local application*

624 Static and phenology-adaptive EOS versions were further compared for a smaller subset with a large elevation gradient
625 (> 1000 m, Fig. 11). The phenology-adaptive technique accounts for the elevation-induced shifts in EOS, and hence, there is
626 more or less one EVI value for the complete elevation range. On the contrary, elevation-induced gradients can be readily seen in
627 the static version, wherein EVI values increase with elevation. In addition, there is also a land-cover class dependent variability in
628 EVI. It needs to be noted that WWF terrestrial ecoregions were used for the stratified boxplots, which are a rather coarse and
629 spatially generalizing description of land cover. Nevertheless, the different classes are clearly separable in the static PBC
630 whereas this variability was reduced with phenology-adaptive compositing. This both applies to the between- and within-
631 ecoregion variability, and thus the phenological harmonization was successfully realized.

632 3) *Global application*

633 Global applicability was demonstrated with a large latitudinal gradient from boreal Russia to South Africa (Fig. 12). Even
634 cross-hemispheric PBCs may be generated and the forests in the same geographic zones are similar for both hemispheres. This is
635 especially striking in the sub-tropical belts, whereas large differences occur in the static PBCs. Phenology-adaptive compositing
636 also minimizes the risk to choose an unfortunate target DOY that might cause severe misinterpretations: the complete sub-
637 continent of Southern Africa seems barely vegetated in the static composite tuned to the northern hemisphere, whereas different
638 savanna, grass and woodland biomes can be resolved in the phenology-adaptive version. Northern hemispheric snow
639 contamination is also a good example of this effect, as a less careful selected target DOY can result in severe snow cover (part
640 c). However, it needs to be noted that the phenology-adaptive version is also not free of snow, although the affected areas are
641 rather unvegetated and are thus of less concern for vegetation-based studies (bare soils and water bodies). Areas that are
642 characterized by a low phenological amplitude (tropics / deserts), are similar in all versions. This is caused by the spectral
643 invariance over the year, and partly a result of the reduced availability of cloud-free observations in tropic regions, which was
644 already discussed before with the wet season Zambian example.

645 4) *Implications*

646 The question arises whether phenology-adaptive or static composites are superior for large area mapping and monitoring tasks,
647 and we recommend considering the compositing method carefully for any given application. For regions that do not feature large
648 gradients or discontinuities in LSP, the overhead in using the more complex phenology-adaptive approach might not be justified,
649 since an LSP dataset at an appropriate spatial scale needs to be derived in the first step. The static approach might also be
650 superior for certain land cover classification tasks, as e.g. the discrimination of crop types partly rely on the phenological phase
651 difference of the growing stages (Van Niel and McVicar 2004). On the contrary, the phenology-adaptive technique phases the
652 crop development, and thus decreases the spectral variability within the crop classes. This feature might improve the separability

653 against other classes such as grasslands, fallows, abandoned land or bare grounds(Griffiths et al. 2013a).The phenology-adaptive
654 approach might also alleviate problems related to within-class differences in LSP across gradients. As an example, tree species
655 classification (Stoffels et al. 2015)would benefit from phenological normalization that accounts for altitude-induced delays of
656 foliage growth.Homogeneous leaf-on composites could also decrease false deforestation detections, as e.g. seasonal variations in
657 broadleaved canopies might erroneously be classified as deforestation if acquired in an unfortunate phenological stage (DeFries
658 et al. 2007).

659 6.4. MODIS vs. Landsat composites

660 The consistency between the MODIS and Landsat PBCs was quantitatively evaluated. It is noted that different spectral
661 response, radiometric pre-processing, view geometry and spatial resolution will inevitably result in differences. However, we
662 assume that the greatest differences occur due to thedifferent temporal resolutions that cause phenological differences.The POS
663 PBCs are characterized by large positive ME values, both for the static and phenology-adaptive version. The mean $|\Delta D|$ is “only”
664 42 (34) days for the phenology-adaptive (static) MODIS PBCs whereas it is 50 (44) days for Landsat (Table 4). Thus, the
665 MODIS PBCs reach farther into the wet season and consequently have higher EVI. The between-sensor MOS PBCs are very
666 similar and all statistics indicate a good agreement (especially ME), which is also reflected in low mean $|\Delta D|$ values (Table 4). In
667 this comparison, the EOS PBC statistics are a bit harder to interpret because of the nature of the two-tailed Gaussian scoring
668 functions, which permits both earlier- and later-than-target observations with higher and lower EVI, respectively. As such, it is
669 possible that an early MODIS observation and a late Landsat observation was chosen, and vice versa, which results in a
670 somewhat larger MAE and RMSE. This is especially driven by the limited data availability of the Landsat system, which might
671 have a bias towards one end: the ME indicates a negative bias which implies that earlier-than-target Landsat observation were
672 preferably chosen (see also Fig. 13). Nevertheless, the statistics indicate a fairly good agreement – especially if compared to the
673 within-sensor EOS PBC statistics. Overall, the quantitative comparison indicates that the between-sensor differences (like
674 radiometry) are indeed within an acceptable range and that differences are mostly a result of temporal characteristics.

675 6.5. Implemented scores

676 Griffiths et al. (2013b) determined the suitability of any observation by a combination of acquisition day, acquisition year and
677 the distance of a pixel to the next cloud or shadow. We expanded on this approach by tuning the inter- and intra-annual criteria
678 with pixel-based phenology and by introducing additional scores to devalue hazy observations, spectral outliers and off-nadir
679 angles. Especially the last criterion was instrumental in generating homogeneous MODIS composites; and although the FOV is
680 narrow and orbital overlaps are small for Landsat, the inclusion of this scoring function also increased the homogeneity at the
681 very edge of the swaths slightly. However, we expect that this effect would be more pronounced in areas with larger overlaps

and with input datasets not featuring a correction for bi-directional effects. The implemented correlation score helped to devalue observations with transient land cover change like flooding or active fires, whereas the algorithm behavior is not strictly defined with regards to permanent land cover change. However, the correlation score is expected to favor the land cover that was observed more often, and the use of LSP ensures that the selected observations are at least in same phenological state – although not necessarily in the same land cover class. The year score and the Y-factor Y_t further reduce the risk of selecting different land covers as target year observations are generally preferred. However, if the data availability in the target year is of concern, it may be favorable to increase Y_t , which may have adverse effects when observing land covers with high inter-annual variability in terms of biomass (e.g. grasslands). We consider our approach flexible with respect to the definition of additional scoring functions, which can be easily integrated into equation 1. Spectral scores that devalue burned or flooded areas might be applicable for specific research questions in our study area, or specific sensors may be devaluated as done by White et al. (2014). Nevertheless, such criteria should be well-considered since the resulting composites will be harder to interpret as they are no longer dominated by temporal characteristics, and the homogeneity might be decreased.

6.6. Time series application

The potential for land cover change mapping was demonstrated by applying the CAT transformation (Hird et al. 2016) to an annual Landsat EOS time series (2001–2012 ± 0) with the phenology-adaptive technique. It needs to be noted that biomass differences between a vegetated and an unvegetated surface are lower than in the POS, which decreases the signal-to-noise ratio of this application (therefore, a national stretch was employed instead of the one Hird et al. (2016) proposed). However, the EOS is optimal to separate trees and grass, whereas their inseparability can mask land cover change in the POS. Even more importantly, it was demonstrated that the EOS PBC quality was high, a requirement that was not met by the POS PBCs. As such, the EOS is a reasonable compromise to identify land cover change processes.

An annual approach was chosen for gradual process identification. This has resulted in an increase in ΔD compared to the five-year cases shown above, and necessitated rigorous filtering of the time series before applying the CAT transform; all observations that deviate more than ± 16 days from D_t were rejected. This allowed to extract the trend parameters with adequate accuracy. The resulting CAT image is free of artifacts, which supports the quality of the approach. The CAT image clearly indicates different change processes, and thus provides a comprehensive picture of the land cover transformations and modifications throughout the past decade. The next step would be to quantitatively map the corresponding change classes and to provide nationwide change statistics, which is out of scope of this paper as this is not a straightforward analysis. As can already be seen with the fairly simple CAT transform, the same change process has to be interpreted within a context. As an example, the gradual increase in biomass shown in Fig. 15 (h-j) is due to regrowth after a large savanna fire, which represents a significantly different ecological meaning than e.g. biomass increase in a forest stand or following agricultural abandonment.

712 7. Conclusion

713 We implemented a parametric pixel-based compositing approach by integrating methods for adapting the compositing process
714 to the land surface phenology of each pixel. The technique can be applied to any kind of gridded EO archive, which we
715 demonstrated for MODIS and Landsat. In both cases, homogeneous and seamless multi-annual composites could be generated
716 across large areas for most seasons. It was shown that the technique is general enough to be applied globally.

717 Seasonal composites can be generated by inputting spatially-explicit LSP layers, and the choice of the scoring functions further
718 increases the flexibility in generating composites representing different phenological phases. The resulting composites were
719 shown to perform a phenological normalization across elevation gradients and land cover classes. As an alternative, fixed DOY
720 composites may also be generated, and the potential application of either method should be considered with care. The inter- to
721 intra-annual data contribution can be controlled by a single parameter which handles the tradeoffs between using data from the
722 target year versus using data that is preferably very close to the target day. We implemented a number of auxiliary scores for
723 specific purposes, e.g. to avoid clouds. The scores can be disabled or enabled in any possible combination and the strength of
724 each score may be adjusted freely.

725 As the Landsat data availability is relatively poor in this part of the world, the temporal improvements of this approach were
726 demonstrated with the daily MODIS product. Wet season composites could not be generated with sufficient precision, however,
727 dry season composite generation was successful. These composites were found to be coherent and homogeneous in most areas,
728 which also applied to analogously generated Landsat composites. Unsurprisingly, the target dates could not be matched as
729 exactly as in the MODIS composites as a consequence of the lower temporal resolution. The quality of the MODIS and Landsat
730 composites, as well as the performance of the phenology-adaptive and static compositing techniques was assured using a
731 quantitative cross-comparison. The generation of a 12-year annual time series demonstrated the feasibility for land cover change
732 and modification mapping. Several change processes were clearly discriminable.

733 Potential applications of the method include for instance the generation of decadal, five-year or annual composites representing
734 the land cover in the same phenological stage for the establishment of national, regional or even global landscape monitoring,
735 reporting and verification systems.

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List of figure captions

Fig. 1. Overview of the study area (Zambia). (a): Digital Elevation Model, acquired by the Shuttle Radar Topography Mission (SRTM). The Worldwide Reference System 2 (WRS-2) is superimposed. (b): Monthly rainfall sums for 2005, obtained from the Africa Rainfall Climatology version2 (ARC2; Novella and Thiaw 2013).

Fig. 2. Number of clear-sky observations for the MODIS (a) and Landsat (b) composites for the five-year period 2003–2007.

Fig. 3. Land Surface Phenology(LSP)for 2005; (a): peak of season (POS), (b): end of season (EOS), (c): minimum of season (MOS). (d): normalized histograms of POS, EOS and MOS (standardized by histogram maximum), and color bar for (a-c). The POS can be at the end or at the beginning of the calendar year, and as such, the data ranges from December 1, 2004 (DOY 336) to December 31, 2005 (DOY 365). The depicted color-ramp is used for all DOY images throughout the paper.

Fig. 4. Schematic illustration of the LSP-adaptive DOY scoring functions. The Gaussian type is shown in (a–d); the logistic S-curves in (e–h). For illustration purposes, we have either visualized fits to the variable LSP with constant function values (a,b,e,g), or have visualized fits to constant LSP but variable function values (c,d,f,h). The chosen LSP and scoring function values are indicated as p_{0-2} and s_{0-2} ; the point signatures indicate the p and s values, and ‘var.’ indicates that a parameter was varied; the variation of the p and s values can be taken from the x- and y-axis, respectively. For consistency with the following real-life examples, the p -values were tagged semantically with POS, EOS and MOS. In all cases, the target metric is the phenological parameter with the highest score, i.e. EOS (a–d), POS (e–f) and MOS (g–h).

Fig. 5. Illustration of the Y-factor Y_f for an arbitrary example. The figure shows isolines of the total score S_T , drawn with a dependence on ΔY and ΔD . The right tail Gaussian type was chosen and two years around the target year are allowed; i.e. $y = 2$. The total score was computed as a combination of the Year score S_Y and the DOY. The higher Y_f , the higher is S_Y – and the smaller is the influence of ΔY on S_T .

Fig. 6. Cloud distance and haze scoring functions; d_{req} was set to 100 pixels.

Fig. 7. Exemplary illustration of the spectral stability assessment and correlation scoring function. (a): mean absolute correlation derived from the temporal correlation matrix, and Landsat-7 NIR image (Path/Row 172/072) affected by sensor anomalies. (b): correlation scoring function.

Fig. 8. View zenith angle scoring function; θ_{req} was set to 40° and 7.5° for MODIS and Landsat, respectively.

Fig. 9. MODIS PBCs for 2005 $\pm$ 2 for POS (a-c), EOS (d-f) and MOS (g-i). Phenology-adaptive and static composites are shown in the first (a,d,g) and second (b,e,h) column, respectively. The depicted band combination is RGB = near infrared, shortwave infrared and red, thus combining complementary information from the three different wavelength domains. The band combination, as well as the same stretch is applied to all reflectance composites throughout the paper. EVI differences between the phenology-adaptive and static composites are shown in the third column (c,f,i); red colors indicate more biomass in the phenology-adaptive composite. The green rectangle in (f) indicates the extent of Fig. 11.

Fig. 10. Temporal characteristics of the composites in Fig. 9. POS (a-b), EOS (c-d), and MOS (e-f) are shown in the rows. The left half of the figure (a,c,e) refers to the phenology-adaptive composites; the right half (b,d,f) to the static composites. For each composite, the selected DOY, the difference to the target DOY ΔD and the difference to the target year ΔY are shown. The same color ramps are applied throughout the paper where appropriate.

Fig. 11. EVI of the MODIS EOS PBC for a sample area (see Fig. 9) with a large terrain elevation gradient (> 1000 m). The phenology-adaptive version is shown in the left column; the static version in the right column. (a-b): EVI maps; the brown-green color ramp is linearly stretched from 0–0.5, (c-d): 2D-histograms between EVI and terrain elevation, (e-f): EVI boxplots for the World Wildlife Fund terrestrial ecoregions (Olson et al. 2001); A–D are Central Zambezian Miombo woodlands, Southern Miombo woodlands, Zambezian and Mopane woodlands and Zambezian flooded grasslands, respectively.

Fig. 12. MODIS PBCs for the target year 2005 across a large latitudinal gradient. The composites are EOS variants, where (b) is a phenology-adaptive composite; (a) and (c) are static composites that were anchored at the average EOS of the Northern (a) and Southern Hemisphere (c). The depicted band combination is RGB = near infrared, shortwave infrared and red.

Fig. 13. Phenology-adaptive LandsatPBCsfor 2005 $\pm$ 2 forPOS (*a-c*), EOS (*d-f*) andMOS (*g-i*). For each composite, the selected DOY, the difference to the target DOY ΔD and the difference to the target year ΔY are shown.

Fig. 14. EVI cross-comparison of the MODIS and Landsat composites for POS (*a-d*), EOS (*e-h*) and MOS (*i-l*). Statistical measures are shown in the columns with mean error (ME), mean absolute error (MAE), root mean squared error (RMSE) and coefficient of determination (R^2) from left to right. The MODIS/Landsat composites are abbreviated with ‘MOD’/‘LND’ and the phenology adaptive and static versions with ‘LSP’/‘STA’, respectively. The residuals are calculated as $e = x - y$; e.g. the lower-left ME value in (*a*) means that the static MODIS composite features higher EVI values than the phenology adaptive Landsat composite. The color ramps are consistent within each column.

Fig. 15. CAT Transformation of the annual EOS Landsat PBCs, mapped to RGB space as Change, Aftereffect, and Trend, respectively. Three exemplary subsets (100 km²) depicting different change processes are shown in (*b-d*; 13.02°S / 30.76°E), (*e-g*; 14.78°S / 27.21°E), and (*h-j*; 16.23°S / 25.79°E) with CAT transformation, 2002 and 2012 composites from left to right.