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Monitoring succession after a non-cleared windthrow in a Norway spruce mountain forest using webcam, satellite vegetation indices and turbulent CO_2 exchange

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ABSTRACT

Forests cover approximately 30% of the world's land area and are responsible for 75% of terrestrial gross primary production. Disturbances, such as fire, storm or insect outbreaks alter the dynamics and functioning of forest ecosystems with consequences, in terms of species distribution and/or gross primary production, not fully understood. Large forest areas are intensively managed and natural disturbances are yet rare events but expected to increase with climate change. Here, we used digital repeat photography to observe the ecological succession in a windthrow disturbed forest in the Bavarian Forest National Park (Germany) and compared it to satellite-derived vegetation indices (NDVI, EVI, and PPI) as well as turbulent CO_2 exchange. A data-driven clustering of the webcam images identified three regions of interest: spruce, grass and a transition region that showed grass in the beginning and became successively overgrown by spruce. The succession was mirrored in trends of annual maxima of gross primary production (GPP), satellite vegetation indices and derived image greenness (green chromatic coordinate, GCC) in the transition region. These trends were also responsible for a positive link between seasonal GPP and proxies. Start and end of growing season were estimated from GCC, NDVI, EVI, PPI, and GPP, compared to each other, and were linked partly to climatological growing season indices and phenological observations. This study demonstrates the suitability and benefits of a webcam in monitoring forest recovery after a severe windthrow event, thus offering a versatile tool that helps to understand successional and phenological processes after a disturbance.

1. Introduction

Forests play an important role in the global carbon cycle (Dixon et al., 1994; Luyssaert et al., 2010) and intact forests ecosystems act as strong carbon sinks (Grünwald and Bernhofer, 2007). With longer vegetation seasons, caused by anthropogenic climate change, a further increase of productivity is expected (Dragoni et al., 2011). However, climate change induced increases in the frequency of disturbances, such as fire, insect outbreaks, and storms, also negatively impacts forest growth (Seidl et al., 2011). Such disturbances can switch an ecosystem from a carbon sink to a carbon source and have the potential to offset any climate change or forest management induced benefits (Seidl et al., 2014). Observing and understanding consequences of disturbances thus plays a key role in understanding ecosystem functioning under climate change.

Major efforts are underway to observe ecosystem carbon fluxes (see FLUXNET, https://fluxnet.ornl.gov/), and also disturbed forest ecosystems are monitored (Lindauer et al., 2014). However, the recently implemented techniques are cost-intensive, depend on flatness of the terrain, homogeneity of the vegetation cover in the footprint area as well as atmospheric conditions (see e.g. Foken et al., 2012), and are thus not ideally suited for large scale observations. An alternative approach is to exploit the links between canopy carbon uptake (net ecosystem exchange, NEE) and phenology (Richardson et al., 2013; Wingate et al., 2015).

One approach is the use of digital repeat photography to directly track the phenological development (Migliavacca et al., 2011). Digital cameras offer many advantages to traditional phenological research (Sonnentag et al., 2012), and are suited to predict NEE dynamics and total productivity but not yet for all plant functional types (Toomey

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et al., 2015). Phenocams (digital cameras used to monitor phenology) are a new but promising technology, mirrored in the large amount of recently published research (Henneken et al., 2013; Julitta et al., 2014; Keenan et al., 2014; Klosterman et al., 2014; Menzel et al., 2015; Morris et al., 2013; Nijland et al., 2014; Petach et al., 2014; Toomey et al., 2015; Wingate et al., 2015).

Remote-sensing of phenology via satellites is another possibility (Fu et al., 2014; Jeganathan et al., 2014; Jeong et al., 2011), and could provide large-scale links between vegetation and CO_2 cycles (Barichivich et al., 2013). However, the correspondence to ground observations is differing by plant species and season (Klosterman et al., 2014; Liang et al., 2011; Misra et al., 2016), and this is where phenocams could fill the gap between automated satellite and manual field observations. Phenocams can also be used to monitor events at the species level, or even for single individual trees (Menzel et al., 2015). Thus, they can provide much higher spatial information than integrated measures, such as satellite observations or turbulent flux measurements.

Phenology is climate sensitive (Dose and Menzel, 2006; Menzel et al., 2006; Richardson et al., 2013), so climatological growing season indices (Linderholm, 2006) seem like another natural choice to estimate the vegetation season (Menzel et al., 2003; Zhang et al., 2004) or carbon uptake (Barford et al., 2001). Bark beetle flight activity was also linked to phenology (Zang et al., 2015) and climate (Baier et al., 2007), and bark beetle induced tree mortality can have severe consequences on forest leaf area index and gross primary production (Bright et al., 2013).

But how climatological indices, phenological observations, phenological estimates derived from near-surface and satellite remote-sensing, bark beetle flight and turbulent carbon exchange are interrelated in disturbed ecosystems is rarely addressed.

To this end, we combined time series of digital camera images with satellite-derived vegetation indices, eddy-covariance measurements of CO_2, climate, phenological observations and bark beetle counts in a windthrow disturbed forest in order to analyze (1) whether it is possible to observe succession using digital camera images, (2) if and to which degree webcam greenness, satellite retrieved vegetation indices, and turbulent CO_2 exchange observations match, (3) how their seasonality is related amongst each other and to climatological growing season indices or phenological observations.

2. Materials and Methods

2.1. Study site

The study site Lackenberg (Fig. 1) is located in the Bavarian Forest National Park (Bayerischer Wald) in south-eastern Germany (13.305°E, 49.100°N, 1308 m a.s.l.). The national park is forested on 98% of its area with a mixed forest dominated by spruce, fir and beech. However, at the altitude of the Lackenberg site, nearly all trees are Norway spruce (*Picea abies* (L.) H. Karst). The area has been heavily damaged by the storm Kyrill on January 18, 2007, and has not been cleared thereafter because of the forest management policy of the national park. The windthrow area at this site is approximately 26.8 ha. Almost all larger trees were uprooted during the storm. The main vegetation, besides surviving spruce trees and newly emerging young trees, consists of grasses (*Deschampia flexuosa* (L.) Trin., *Luzula sylvatica* (Huds.) Gaudin, *Juncus effuses* L.), fern (*Athyrium distentifolium* Tausch ex Opiz), few blue berries (*Vaccinium myrtillus* L.) and very few rowan berries (*Sorbus aucuparia* L.). In 2009 a tower was set up in the middle of the windthrow area, with instruments to measure turbulent CO_2 exchange (Lindauer et al., 2014), and in 2010 a webcam was mounted.

2.2. Webcam images setup

From May 2010 to July 2016, digital images were taken by a dual-sensor security webcam Mobotix M12 (Mobotix AG, Langmeil, Germany), which records near-infrared (NIR) and standard RGB images at the same time with slightly different fields of view. The camera was run in full automatic mode (exposure, aperture, and white balance) and was set up according to standard recommendations (Richardson et al., 2007; Sonnentag et al., 2012): camera facing north; gray scale reflectance panel (Fluorilon, Avian Technologies, New London, NH, USA) in field of view; multiple images taken each day between 12am and 1pm CET. We hoped to use the gray panel and the NIR image to calculate a pseudo-NDVI (normalized difference vegetation index), which, however, did not yield any sensible results. Because of hardware failure, at the end, only one backup image per day, taken at midday, with 640 × 480 pixels was available for analyses throughout the whole period. Additionally, not all images were (fully) transmitted due to network failures and we discarded all images that were empty or only partially transmitted.

The camera was moved multiple times during the study period, resulting in different views of the study site. Images were registered using open-source image-processing software Fiji (www.fiji.sc) in order to show the same view over the whole study period (see Fig. S1). Then, images were cropped to the common region excluding the gray panel, which was not registered successfully because it was too near to the camera compared to the background forest.

2.3. Automatic extraction of webcam image regions of interest (ROI)

For further analyses the webcam images were segmented into regions of interest (ROIs) with an approach proposed by Bothmann et al. (2017), which defines ROIs in an automated and data-driven way. The so-called 'unsupervised ROI approach' (uROI) is implemented in the R package phenofun (Bothmann, 2016) and works as follows.

Let x_t denote a three-color RGB image with $m*n$ pixels at time t (with a total of T images), $x_t \in \mathbb{R}^{m \times n \times 3}$that is $\overline{x_t} \in \mathbb{R}^{3mn}$First, each image is rearranged into a long vector $\overline{x_t} \in \mathbb{R}^{3mn}$. Then the entire image data is stored in a matrix X, where each column of X corresponds to one image, that is $X = (\overline{x_1}, \ldots, \overline{x_T}) \in \mathbb{R}^{3mn \times T}$. Then, a truncated version of a singular value decomposition (SVD) of X is carried out to reduce dimensionality by only computing the first p singular vectors. This leads to a decomposition of X into $X = UDV'$, with $U \in \mathbb{R}^{3mn \times p}$, $D \in \mathbb{R}^{p \times p}$, $V' \in \mathbb{R}^{p \times T}$, where the columns of U are the eigenvectors of XX' and may be called eigenimages. Then, U is rearranged into a matrix $\overline{U} \in \mathbb{R}^{mn \times 3p}$, such that each pixel is described by $3p$ variables. Based on $\overline{U}$, the pixels are clustered with a k-means clustering algorithm leading to a pre-specified number of K clusters. After testing

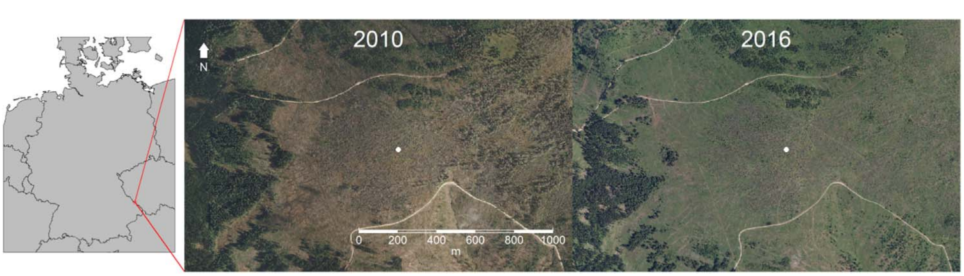

Fig. 1. Aerial images of the study site (courtesy of the Bavarian Forest National Park). The white dot in the middle is the location of the tower, where the webcam and other instruments were mounted. The windthrow area is located between the two roads, roughly a circle with 400 m radius around the tower. The strip left of the windthrow area besides the dense forests, was cleared in 2009 and 2010 after a massive bark beetle infestation in order to prevent a further spreading.