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Estimating wheat biomass by combining image clustering with crop height

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ABSTRACT

Site-specific management strategies in wheat fields can be strongly enhanced with sensor technology that detects spatial changes of wheat biomass. The objectives of this study were to propose a multi-sensor approach combining a digital camera system that measures plant coverage with an arbitrary crop height measuring instrument for estimating wheat biomass. Digital images, fresh and dry biomass, and crop height measurements were taken at 180 sample points distributed over 4 fields between the BBCH growth stages 30–75. Plant coverage percentage was calculated by separating plant pixels from background pixels of NDVI and NIR images using image segmentation based on partitioning clustering. Performance of three clustering algorithms (k-means, partition around mediods (PAM), and fuzzy c-means) was analyzed. Plant coverage from image clustering was further related to fresh and dry biomass with and without crop height measurements using simple and multiple regression models. The performance of the three clustering algorithms was similar for estimating wheat biomass. NDVI image segmentation was highly obstructed by scattering effects especially at later BBCH stages through the presence of wheat ears, stems, and tilted leaves, whereas NIR image segmentation was generally good except with images that were taken at locations with very low plant coverage and dry soil crusts. Consequently, NIR image clustering yielded more accurate estimates of fresh and dry biomass ($R^2 = 0.79/0.68$) than NDVI image clustering ($R^2 = 0.66/0.56$) among the individual measurement runs on average. Still cloud conditions had some influence on NIR clustering. By pooling the complete set of sampling points from all measurement runs into a global model, the combination of image clustering with crop height was helpful. For fresh biomass, global model quality changed from $R^2 = 0.15$ or $R^2 = 0.46$ without crop height to $R^2 = 0.63$ or $R^2 = 0.82$ with crop height for NDVI or NIR, respectively. For dry biomass, crop height was itself a strong predictor with $R^2 = 0.86$, whereas the model improvement by including image clustering of plant coverage was nearly negligible. In conclusion, the combination of a camera sensor using image clustering with a sensor able to measure crop height such as LIDAR or ultrasound systems seems to be a promising way to reach for more accurate and robust estimations of wheat biomass especially when measurements over multiple fields and dates are considered without the need of re-calibration.

1. Introduction

The high spatial variability within fields has been widely stated for soil and plant agronomical parameters (Dammer, 2005; Schirrmann and Domsch, 2011). This is especially true for the growth of wheat plants because it is influenced by a complex interrelation of many factors comprising amongst others soil heterogeneity, dispersal of weeds, plant diseases, relief position, or management (Lemaire and Gastal, 1997). Thus, spatial patterns of wheat biomass are highly heterogeneous and highly temporally unstable. Sensor technology may detect changes of wheat biomass online in order to adapt site-specific management strategies and once implemented it might help to improve nitrogen management, fungicide application, crop yield estimation, and crop monitoring (Oerke et al., 2010). In case of precision fungicide application, one would be interested in estimating the right amount of spray liquid according to the biomass and crop surface (leaves and stems) of wheat plants (Dammer and Ehlert, 2006). Currently, no commercial sensor exists that allows automatic disease detection

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before the pathogen reaches critical thresholds. However, since crop surface and fresh biomass correlate strongly with each other, the sensor detection of one of these two agronomical parameters is often sufficient for variable rate application of fungicides.

Optical sensors operating in the visual (Vis, 400–700 nm) and near-infrared (NIR, 700–1300 nm) wavelengths of the electromagnetic spectrum are frequently used in determining field heterogeneity for precision agricultural applications (Dammer and Ehlert, 2006; Schirrmann et al., 2013). Both active and passive sensors are used in order to estimate many agronomical parameters of wheat plants often with the focus on nitrogen management (Erdle et al., 2011; Schirrmann et al., 2015). Passive sensors measure directly a signal prompting from the wheat plants using mostly the sunlight reflected from the plant leaf surfaces (Erdle et al., 2011). Many remote sensing-, unmanned aired vehicle- and camera-based ground systems work this way (Bendig et al., 2014; Dammer, 2005; Lopresti et al., 2015). In contrast, active sensors use an artificial signal directed to the wheat plants and its response is measured after it is scattered back from the plant surfaces. Several types of signal sources have been tried such as light emitting diodes, LED (Dammer and Wartenberg, 2007), laser (Ehlert and Heisig, 2013), or ultrasonic devices (Anthony et al., 2014). The advantage over passive sensors is that active sensors become to a certain degree independent of environmental influences such as ambient light during the measurement (Kipp et al., 2014). Examples of commercially active sensors include the Yara N-Sensor® (Yara, Dülmen, Germany), GreenSeeker® (Trimble, Sunnyvale, CA., USA), OptRx (Ag Leader Technology, Io., USA), CropCircle® (Holland Scientific Inc., Lincoln, NE, USA), detectspray® (Blackshaw et al., 1998) based on the weedSeeker®, and Weed-IT® (Rometron, Doorwert, NL) based on fluorescence. However, each of these sensors delivers an integrated signal over the entire measuring area that means a mixture of plants and soil. In contrast, measurements of plant biomass with camera sensors are able to differentiate the measuring area pixelwise.

Often, the normalized difference vegetation index (NDVI) is derived from optical sensors and related to several agronomic parameters including wheat biomass. The NDVI is calculated as the normalized transformed ratio between the reflectance measured at the red wavelength range (RED, 620–700 nm) and NIR wavelength range (Rouse et al., 1974).

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})} \tag{1}$$

The NDVI uses the advantage that back-scattering from plant components is very low in the RED whereas very high in the NIR. The low back-scattering in the RED occurs due to chlorophyll activity of photosynthesis. In contrast, the high NIR reflectance is strongly determined by the scattering of light in the spongy mesophyll of the plants at water saturated cell walls, in air-cell interfaces between cell components, or other cells and can therefore be well related to the plant biomass (Campbell, 2002). As a result, there is a high difference between RED and NIR reflectance from the crop canopy. On the contrary, soil reflectance, has only a small difference between RED and NIR wavelengths. This makes it easy to distinguish between plant and soil using the NDVI (Lukina et al., 1999). Because of these properties, the NDVI was related to numerous agronomical parameters of wheat such as leaf area index (LAI), biomass, or used in crop models.

A key role for estimating wheat biomass from digital images is the correct separation of wheat plants from the background, usually the soil, by means of image segmentation. The image segmentation is the process of partitioning an image into a set of disjoint segments so that image pixels of a specific segment share certain characteristics with each other based on the texture, color, or intensity (Kandwal et al., 2014). The aims of image segmentation are to simplify the image, exclude the background or to clarify certain features in the image. Many different types of segmentation methods are used in image processing such as thresholding, clustering, histogram based methods, or neural networks (Kandwal et al., 2014; Moshou et al., 2001). Most studies that estimate agronomical parameters of wheat from digital images are based on thresholding. These approaches use empirically presumed threshold values that split image gray-scaled values to differentiate background and plant pixels (Jones et al., 2004; Lukina et al., 1999; Tavakoli et al., 2014). Guo et al. (2013) used a machine learning approach with regression trees in order to segment vegetation in wheat images. So far, partitioning clustering has not been adopted for wheat image segmentation, although it has been used successfully in many other research fields like medical imaging or document imaging (Feng and Chen, 2004).

In this study, the general research question was to propose a multi-sensor approach for in-field estimation of wheat biomass in the field. By doing so, we tested a camera based solution using images from the RED and NIR wavelength range and calculated the wheat plant coverage over its field of view (FOV) by means of image clustering. The plant coverage was further combined with crop height measurements to find a solution for a future camera sensor fusion with a height measurement instrument based on LIDAR or ultrasonic to measure wheat biomass online. We investigated the following research questions:

– Can we estimate wheat biomass from NDVI or NIR image clustering?
– Do we need calibration before using the camera sensor on a different field or date?
– Does the partitioning clustering algorithm influence model results?
– Is modeling improved by integration of crop height in the model for a future sensor fusion?

2. Material and methods

2.1. Data acquisition

The on-farm study was conducted in four fields in Eastern Germany during the spring season in 2014 (51° 49′, 12° 42′). The soils of these fields are characterized by young flood plain deposits of the Elbe river influenced by groundwater. Especially, different proportions of soil texture fractions led to variations in plant growth. Winter wheat with different varieties was grown from field A to D (Table 1): *Asano*, *Glaucus*, *Kerobino*, and *Potential*. In each field, three measurement runs on different dates were conducted between the BBCH growth stages 30 and 75 (Lancashire et al., 1991). For each measurement run, 15 locations in a transect were chosen with respect to the wheat variability visually observed at that date and field (Fig. 1). Since biomass sampling was destructive, reference points for the next measurement run

Table 1
Field characteristics.

Field	Size (ha)	Wheat variety	Dominant soil type	Soil texture range
A	13.7	Asano	Fluvic Cambisol	Sandy loam – loamy sand
B	28.2	Glaucus	Fluvic Cambisol	Silt loam – sandy clay loam
C	64.9	Kerobino	Fluvic Cambisol	Silt loam – clay loam (partly loamy sand)
D	15.5	Potential	Fluvic Cambisol	Silt loam – clay loam