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Optimization of UAV-based imaging and image processing (orthomosaic and point cloud) approaches for estimating biomass in forage crop

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ABSTRACT. Field forage pea is an essential source of nutrients for livestock diets, and high-quality field peas can influence livestock health and reduce greenhouse gas emissions. Above-ground biomass (AGBM) is one of the vital traits and primary yield components in field forage pea breeding programs to evaluate biomass quantity. However, a standard method of AGBM measurement is a destructive and labor-intensive process. This study utilized an unmanned aerial vehicle (UAV) equipping with a true-color RGB and a 5-band multispectral camera to estimate the AGBM of the winter forage pea in three breeding fields. Three processing techniques: vegetation index (VI), digital surface model (DSM), and 3D reconstruction model from point clouds, were used to extract the digital traits to estimate the AGBM. The correlation coefficient and linear regression were performed between the standard AGBM measurement and different methods with different crop height and volume extraction parameters. The results showed that the crop volume from the 3D model-based method (alpha shape, α: 1.5) of UAV-RGB imagery’s point clouds provided the consistent and high correlation with the AGBM: fresh AGBM (r = 0.78 – 0.81, p < 0.001) and dry AGBM (r = 0.70 – 0.81, p < 0.001), comparing with other methods from three locations. For the crop height relationship, the DSM-based method (height at 95th percentile) performed consistent and high correlation (r = 0.71 – 0.95, p < 0.001). By using the UAV imagery, the proposed approaches demonstrated the potential of estimating the AGBM of winter forage pea breeding fields across multiple locations.

Keywords. Above-ground biomass, unmanned aerial vehicle (UAV), vegetation indices (VI), digital surface model (DSM), 3D reconstruction model.
Introduction

Field pea (Pisum sativum L.) is an annual cover crop providing multiple benefits to production agriculture such as weed suppression, erosion control, nitrogen fixation, and increased soil organic matter. Field pea, importantly, provides numerous benefits as food in the form of dry seed, vegetable, and feed/fodder. As a forage, field pea is a high-yielding, short-term crop with a high protein content (Fraser et al., 2001; Chen et al., 2006; Clark, 2007; Tulbek et al., 2017). Similarly, field pea is a highly palatable grain for all classes of livestock with nutrient-dense energy and protein source. The animal feed represents the highest proportion of variable costs in most livestock systems, and livestock farming practices contribute to environmental impacts. Especially, grazing is one of the activities that cause a severe negative effect by contributing 14.5% of all anthropogenic sources of atmospheric methane emissions over the globe (Steinfeld et al., 2006; Gerber et al., 2013). Therefore, breeding programs aim to continuously improve field pea varieties that are well-adapted to the local environment and produce high quantity and quality biomass. Furthermore, developing/increasing suitable nutrients on forage converted into animal products (meat or milk) and decreasing methane produced from cattle digestion of feed. This is essential to maximize growers/ranchers’ profitability and reduce greenhouse gas (Annicchiarico et al., 2019; Insua et al., 2019; Ligoski et al., 2020).

In the field pea breeding program, the above-ground biomass (AGBM) is one of the critical performance phenotypes/trait that can be used to assess the nutrition status and the primary yield component for a cover/forage crop (Quirós Vargas et al., 2019). Traditionally, the AGBM and other morphological/physiological characteristics on a large number of crop genotypes are measured manually, which is laborious and prone to errors (Furbank and Tester, 2011; Cobb et al., 2013; Maesano et al., 2020). Currently, remote sensing technologies have been adapted and utilized as tools/solutions to phenotype in the breeding program in a non-destructive manner, with the ability for high-throughput data acquisition (Jung et al., 2021; Li et al., 2021; Ortiz et al., 2021; C. Zhang et al., 2021).

Unmanned aerial vehicles (UAVs) have increasingly been used as a sensing platform that can be applied to extract structural characteristics of crop/trees and quantitative assessment (de Jesus Colwell et al., 2021; Guo et al., 2021; Sangjian et al., 2021; H. Zhang et al., 2021). The UAV integrated with multispectral cameras have been used to evaluate the crop AGBM utilizing vegetation indices (VIs) in barley (Tilly et al., 2015; Wengert et al., 2021), dry bean (Sankaran et al., 2018), rice (Zheng et al., 2019; Wan et al., 2021), and wheat (Yue et al., 2019; Choudhury et al., 2021). Besides, with UAV and the digital red-green-blue (RGB) camera, the digital surface model (DSM) constructed using the structure from motion (SfM) algorithm (Schonberger and Frahm, 2016) has been applied to estimate AGBM in cotton (Thompson et al., 2019), maize (Niu et al., 2019; Gilliot et al., 2021), oat (Acorsi et al., 2019), rice (Ortiz et al., 2021; Peprah et al., 2021), soybean (Maimaitijiang et al., 2019; Toda et al., 2021), and wheat (Yue et al., 2017; Banerjee et al., 2020).

In general, VIs represent digital AGBM based on the spectral reflectance characteristics of the top crop surface. In regard to the DSM approach, the model is employed for extracting digital traits from different dimensions to quantify crop morphological traits. The one-dimensional (1D) data include traits such as crop height and crop width or area, the two-dimensional (2D) data include traits such as crop volume, and both types of data can be associated with the AGBM (Banerjee et al., 2020; Di Gennaro and Matese 2020). Nevertheless, the accuracy of biomass estimation may be affected by saturation effects (environmental/equipment conditions) on the VIs data (Reddersen et al., 2014) or the impotence of the RGB camera. Including the precision of the method used to create the digital terrain model (DTM, which refers to the topology of the ground where the crop is grown) for extracting crop height from DSM (Bendig et al., 2014; Rogers et al., 2020). In recent years, with the advancements in the SFM algorithm and dense-image-matching techniques, three-dimensional (3D) point clouds can be generated from UAV-based RGB imagery. The digital traits, especially canopy volume in tree species, based on the 3D reconstruction models (convex hull, concave hull, alpha shape, and voxel grid) from point clouds captured by RGB camera, have performed better than the DSM-based approach, serving as a simple alternative compared to the expensive LiDAR (Light Detection and Ranging) sensor systems (Dong et al., 2021; Kothawade et al., 2021; Qi et al., 2021). However, these techniques’ applicability in field crops remains yet to be evaluated.

Therefore, in this study, three techniques were utilized to estimate the AGBM in winter field pea breeding trials, namely using vegetation indices, digital traits extracted from DSM, and 3D model-based techniques on data extracted from UAV imagery. The specific objectives were to: (1) develop pipelines to segment vegetation point clouds from the soil surface/weeds, reconstruct point clouds of individual plots, and extract digital traits utilizing the point clouds constructed from UAV-based RGB imagery; and (2) explore the potential of utilizing the three different approaches for extraction the digital traits to assess AGBM of individual winter pea-breeding plot

Material and Methods

Study Area

The winter pea breeding trials were located in the Palouse area of Northwestern, USA. The trials were spread across two years/seasons. In the year 2019, the Austrian winter pea advanced yield trial (referred to as panel 1921) was located in two...
locations – Genesee, ID, and Garfield, ID. In the year 2020, the forage and cover crop winter pea advanced yield trial (referred to as panel 2021cc) was located at Pullman, WA. These three trials were used in this study, as presented in Figure 1. The plots were arranged in a randomized complete block design with three replicate plots of each breeding line/entry (10 entries for panel 1921, 9 entries for panel 2021cc) and relevant commercial check (total individual plot = 126). The individual plot size was approximately 1.5 × 5.0 m.

Data Acquisition

Digital traits in this study were generated through UAV imagery. The multispectral images were acquired from AgBotTM (ATI/Aerial Technology International, Oregon City, OR, USA) mounted with a 1.2-megapixel RedEdge camera (Micasense Inc., Seattle, WA, USA). The UAV’s flight mission was a single grid with 80% front and 70% side overlap to capture images, and the UAV was operated at 2 m/s flying speed at 20 m flight altitude, and these parameters were set using Mission Planner software (http://ardupilot.org/planner; accessed on Jan 5, 2022). A summary of the flight details is provided in Table 1.

| Season | Field Location | Growth Stage | UAV’s Flight – Image Acquisition | Ground Reference Data |
|--------|----------------|--------------|---------------------------------|-----------------------|
|        |                |              | Date | Flight Altitude (m) | Camera | GSD [a] (cm/pixel) | Fresh AGBM [b] | Dry AGBM |
| Genesee | F50 [c]        | F50          | Jun 18 | 10 | RGB [d] | 0.21 | Jun 19 | - |
|         |                |              | 20    | RGB | 0.50 | - | - |
|         | MS [e]         |              | 20    | RGB | 1.34 | - | - |
|         | PM [f]         |              | Jun 29 | 10 | RGB | 0.19 | - | Jul 31 |
|         |                |              | 20    | RGB | 0.51 | - | - |
| Garfield | F50            | F50          | Jun 24 | 10 | RGB | 0.22 | Jun 25 | - |
|         |                |              | 20    | RGB | 1.19 | - | - |
|         | MS             |              | 20    | MS | 0.21 | - | Jul 31 |
|         | PM             |              | Jul 29 | 10 | RGB | 0.21 | - | Jul 31 |
| Pullman  | F50            | F50          | Jun 10 | 10 | RGB | 0.25 | Jun 12 | - |
|         |                |              | 20    | RGB | 0.51 | - | - |
|         | MS             |              | 20    | MS | 1.26 | - | - |
|         | PM             |              | Jul 27 | 10 | RGB | 0.29 | - | Jul 27 |
|         |                |              | 20    | RGB | 0.55 | - | - |

[a] GSD: ground sampling distance; [b] AGBM: above-ground biomass; [c] RGB: red-green-blue [spectral band range from 390 to 700 nm]; [d] F50: 50% flowering; [e] MS: multispectral camera [Spectral bands were blue: 475 ± 10 nm, green: 560 ± 10 nm, red: 668 ± 5 nm, red edge: 717 ± 5 nm, and NIR: 840 ± 20 nm]; [f] PM: physiological maturity

DJI-Phantom 4 Pro with a 20-megapixel onboard RGB camera (DJI Inc., Los Angeles, CA, USA) was used with a similar flight pattern as the AgBOTTM system to collect RGB data, except that the flight plan was programmed using Pix4Dcapture (Pix4D S.A., Lausanne, Switzerland) and two flight altitudes were assessed, 10 and 20 m. During each flight, a 0.3 × 0.3 m white reference panel having 99% reflectance from RGB to near-infrared (NIR) spectral range (Spectralon® Diffuse
Reflectance Targets, SRS-99-120, Labsphere Inc., North Sutton, NH, USA) was placed in the field for radiometric correction. The ground reference data (actual AGBM through harvest) were acquired at 50% flowering (F50, 50% of the winter pea in the individual plot have flowers, at anthesis). The average crop height and fresh biomass of the full or entire plot area and the specific plot area (~1.5 × 1.5 m, refers to specific plot area harvested at 50% flowering as representative data) was evaluated at this stage, as the crops have high biomass at this stage. In forage crops, this stage is also critical as the crops will be harvested at this stage of growth as plants would have accumulated maximum biomass, which would translate to maximum productivity. In addition, ground reference data was also acquired at the physiological maturity (PM) stage, where the dry AGBM was monitored for the remainder of the crop in each plot.

**Image Processing**

RGB and multispectral images from UAV were pre-processed by the Pix4Dmapper photogrammetry software (Pix4D S.A., Lausanne, Switzerland) to derive an orthomosaic image (*.tif file) from both datasets. The software automatically utilized the scene illumination, reference panel, and sensor specifications to improve the orthomosaic images’ radiometric quality. These processes are vital to create the surface reflectance imagery (*.tif file) from a multispectral camera to construct VI images with consistent light quality and better data comparisons. Furthermore, for RGB images, the software could also be used to generate the DSM (*.tif file) and point cloud (*.las file) data. These three raw data files (orthomosaic, DSM, and point cloud) were processed to extract the digital traits, as presented in Figure 2a.

![Image Processing Diagram](image)

Figure 2. Image processing pipeline: (a) flowchart of overall pipelines used to extract digital traits in this study, (b) a VI data extraction pipeline, and (c) a crop height data extraction from DSM pipeline. SAVI: Soil adjusted vegetation index; OBIA: object-based image analysis; NIR: near-infrared; RE: red edge; CIre: chlorophyll index red edge.
Vegetation Indices

The multispectral surface reflectance images were used to construct VIs utilizing the customized algorithm in Python 3 using the Rasterio library (https://rasterio.readthedocs.io/en/latest/#; accessed on Jan 5, 2022), as described in Figure 2b. The 12 VIs, especially those commonly used in agriculture and showing potential to estimate AGBM productivity, were derived (Table 2).

| Vegetation Index | Formulation | Reference |
|------------------|-------------|-----------|
| Clgr: Chlorophyll Index Green | $\frac{\text{NIR} - \text{Green}}{\text{Green}}$ | Gitelson et al. (2003) |
| C Ire: Chlorophyll Index Red Edge | $\frac{\text{NIR} - \text{Red}}{2.5 \times (\text{NIR} - \text{Red})}$ | Gitelson et al. (2003) |
| EVI2: Enhanced Vegetation Index 2 | $1 + \frac{\text{NIR} + (2.4 \times \text{Red})}{\text{NIR} - \text{Green}}$ | Z. Jiang et al. (2008) |
| GNDVI: Green Normalized Difference Vegetation Index | $\frac{\text{NIR} - \text{Green}}{\text{Green} + \text{NIR}}$ | Gitelson et al. (1998) |
| MCARI2: Modified Chlorophyll Absorption Ratio Index 2 | $1.5 \times (\frac{2.5 \times (\text{NIR} - \text{Red})}{\text{Green} + \text{NIR}} - \frac{1.3 \times (\text{NIR} - \text{Green})}{\text{Green} + \text{NIR}})$ | Haboudane et al. (2004) |
| MTVI2: Modified Triangular Vegetation Index 2 | $\sqrt{(2 \times \text{NIR} + 1)^2 - (6 \times \text{NIR} - 5 \times \sqrt{\text{Red}}) - 0.5}$ | Haboudane et al. (2004) |
| N DRE: Normalized Difference Red Edge | $\frac{\text{NIR} - \text{Rededge}}{\text{NIR} + \text{Rededge}}$ | Gitelson and Roujean and Breon (1995) |
| NDVI: Normalized Difference Vegetation Index | $\frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}$ | Rouse et al. (1974) |
| NDWI: Normalized Difference Water Index | $\frac{\text{Green} - \text{NIR}}{\text{Green} + \text{NIR}}$ | McFeeters (1996) |
| OSAVI: Optimized Soil Adjusted Vegetation Index | $\frac{\text{NIR} + \text{Red} + 0.16}{\text{NIR} - \text{Red}}$ | Rondeaux et al. (1996) |
| RDVI: Renormalized Difference Vegetation Index | $\sqrt{(\text{NIR} + \text{Red})}$ | Roujean and Breon (1995) |
| RGBVI: Red-Green-Blue Vegetation Index | $\frac{\text{Green}^2 - (\text{Blue} \times \text{Red})}{\text{Green}^2 - (\text{Blue} \times \text{Red})}$ | Bendig et al. (2015) |

The soil mask layer was generated using the soil adjusted vegetation index (SAVI, Huete 1988) and was applied to eliminate the soil surface from each VI image. The polygons defining each crop plot consisting of six subplots (1.35 × 0.75 m for a subplot, two subplots covered the harvested fresh biomass area) for evaluating crop at the F50 stage and four subplots at the PM stage (Figure 1, 2b, 2c, and 8, remaining plot area) were digitized in a shapefile (*.shp) format using open-source software Quantum GIS (QGIS, version 3.20.3). The subplot polygons were shaped such that the estimated crop volume (CV) was a similar area as the standard (harvested) AGBM data. The plot segmentation shapefiles were imported to the customized algorithm. Then, image features such as maximum (Max), average (Mean), sum, standard deviation, 95th percentile, 90th percentile, 85th percentile (highest data value remaining after 5%, 10%, and 15% of the data is removed were extracted from CHM, respectively, referred to as 95P, 90P, and 85P), total area (total area of a region of interest in terms of the number of pixels), and canopy area (canopy cover/area within a region of interest in terms of the number of pixels) of each subplot within each VI images were extracted with the Python libraries: NumPy (https://numpy.org/; accessed on Jan 5, 2022) and Rasterstats (https://pythonhosted.org/rasterstats/#; accessed on Jan 5, 2022). These data features extracted from each subplot (labeled during the plot segmentation creation process) were exported as comma-separated values (CSV) file format. The image feature data (e.g., maximum, mean, standard deviation, 95P, 90P, and 85P) were further analyzed to compute VI area data (referred to in Fig. 2a) by multiplying the parameter (image feature data) with the crop coverage area (the ratio between canopy area and total area). These parameters were computed for Specific Area (two subplots harvested at flowering) and Full Area (total of six subplots).

Crop Height Model from Digital Surface Model

The DSM (height above mean sea level, m) from RGB imagery was used to create a crop height model (CHM) to represent the height of the winter pea of each subplot before estimating the crop volume, as shown in Figure 2c. The process starts with constructing the digital terrain model (DTM), a terrain surface topography, using QGIS software. The software extracts the elevation and coordinate information of the targeted points on the DSM’s soil surface. This information serves as an input into the triangulated irregular network (TIN) algorithm to generate a DTM (*.tif file) of the field extent (Q. Jiang et al., 2019; Ortiz et al., 2021). Then, the pixel-wise subtraction of the DTM from the DSM was performed to construct a CHM using Python 3. In this process, the threshold (height above ground level) was set at 0.05 m to remove the pixels lower than the threshold—considering weeds or other noises. Similar to VI data extraction processes, the plot segmentation shapefile were employed on the CHM layer to acquire crop height (CH) statistical data for each subplot. The crop coverage area data were multiplied with the CH data to acquire CV data for each subplot of the Specific and Full Area.
Reconstruction Model of Point Clouds

The generated point cloud data from RGB imagery was comprised of non-pea materials such as soil surface and weeds, as shown in Figure 3a.

![Diagram of image processing pipeline for 3D reconstruction model: (a) pipeline used to segment the point clouds of individual winter pea plot, and (b) pipeline used to reconstruct 3D models to extract crop volume.](image)

Figure 3. Image processing pipeline for 3D reconstruction model: (a) pipeline used to segment the point clouds of individual winter pea plot, and (b) pipeline used to reconstruct 3D models to extract crop volume.
The first processing step was to separate the winter pea plot from these objects prior to reconstructing a 3D model to calculate CV. Object-based image analysis (OBIA) technique was approached on the orthomosaic RGB image to classify the winter pea and non-winter pea objects. QGIS software with the Orfeo ToolBox plugin (https://www.orfeo-toolbox.org/; accessed on Jan 5, 2022) was utilized to implement the OBIA. The watershed segmentation algorithm combined with supervised classification using the image classification algorithm from the support vector machine classifier were applied to segment and classify the objects on the winter pea field image. Duarte et al. (2018) described the process in more detail. The result from OBIA was a shapefile with four types of a classified polygon (winter pea, soil surface, shadow, and other objects). Therefore, only the vegetation (winter pea) polygon was selected and converted to another shapefile. Further, the point cloud data was clipped with the vegetation shapefile to get the point clouds of the vegetation (*.las file), mainly–winter pea plot on the field (Figure 3a). Next, the plot segmentation shapefiles of each plot were applied to clip/segment the vegetation point clouds to get a single plot of winter pea using a customized Python 3 script utilizing the WhiteboxTools library (https://www.whiteboxgeo.com/; accessed on Jan 5, 2022). Furthermore, CloudCompare software version 2.11.3 Anoia (https://www.danielgm.net/cc/; accessed on Jan 5, 2022) was occasionally used to check and remove extreme point clouds above and around the plot in this process.

The digital traits were extracted from the point clouds of individual winter pea plots (Figure 3b). These single plots (45, 45, and 36 plots for Geneseed, Garfield, and Pullman, respectively, at one growth stage) were loaded to a customed algorithm in MATLAB R2021b (The Math Works Inc., Natick, MA, USA). All points were projected on the X-Y plane, and the tallest winter pea height as a maximum CH (Max) and tallest at 95% percentile (95H) of the CH were extracted from the point cloud position in the Z plane, Figure 3b. Furthermore, the difference between the point cloud positions in the Z plane at maximum and 5% percentile (Max-5H) and at 95% and 5% percentile (95H-5H) were also calculated, which minimizes the effect of the plot’s inclination. Before reconstructing the 3D model, more point clouds on the plot surface were created by the interpolation method on the point clouds within each

Data Analysis

The correlation analysis was performed between digital traits extracted from UAV imagery with three techniques (VI, DSM, and 3D model) and ground reference data (harvested biomass). The digital traits extracted from RGB imagery of different flying altitudes (10, 20 m) of data collection, including the digital traits extracted from different areas (Full and Specific plot area), were also considered. Simple linear regression analyses were conducted between both data sources, and the coefficient of determination ($R^2$) and the root mean squared errors (RMSE) were calculated for the techniques presented consistent correlation coefficient value of all three locations.

Result and Discussion

Biomass Data

Ground reference data in the form of AGBM were acquired at 50% flowering and at harvest. As shown in Figure 4, the plant height at the flowering stage ranged from 0.4 to 1.1 m. The average CH and biomass in the Pullman trial were higher than those from Geneseed and Garfield trials (0.80 m). The plant materials (trial type) and weather during the growing season (2020 being one of the best crop growing seasons with sufficient rainfall and cooler summer temperatures) could have resulted in these observed differences.
Figure 4. Ground reference data from the standard methods on the three locations - Genesee, Garfield, and Pullman (a) crop height, (b) fresh above-ground biomass, and (c) dry above-ground biomass. μ: mean; σ: standard deviation; AGBM: above-ground biomass.

Crop Height Estimation

**DSM-Based Technique for Crop Height Estimation**

The extracted CH from two flying altitudes of data collection extracted using two processing techniques (DSM and point clouds) was evaluated by comparing with CH from the standard method (manual measurement) through the Pearson correlation coefficients shown in Figure 5a. The DSM-based techniques’ 95th percentile CH showed consistent and high correlation ($r = 0.71 - 0.95$, $p < 0.001$) with the standard measurement of all datasets. Further, CH extracted by the DSM-based technique of different flight altitudes did not present a clear difference in correlation coefficient results. However, the results from CH in the full or entire plot area of estimation were slightly higher than the specific area, which is reasonable as the standard method considered the CH from the full plot area. Based on the linear regression, 95th percentile CH from the DSM-based technique extracted on a full plot area of the data collected at 20 m altitude were performed as the correlation coefficient presented high and consistent for all three trial locations (Figure 5b). High accuracy at Genesee ($R^2 = 0.87$) and Pullman ($R^2 = 0.86$), while a moderate estimate at Garfield ($R^2 = 0.60$) as a few predicted data was out of estimation range. RMSE was only $0.05 - 0.07$ m for these three locations, suggesting a high accuracy and repeatability of CH estimates.

CH estimation accuracy from DSM-based technique relates to the DSM from UAV imagery constructed over the SfM algorithm, which relies on various aspects such as the visible surface complexity, resolution and radiometric depth, son-object-sensor geometry, and sensor type (Fonstad et al., 2013; Banerjee et al., 2020). DTM layer also affects the accuracy of CH estimation. DTM from the SfM algorithm was constructed by detecting the lowest terrain surface topography on the image, which means that the sensor should capture the bare earth surface, and the height of objects and bare earth surface should show high contrast to get a reliable DTM layer (Jensen and Mathews 2016; Salach et al., 2018). Accordingly, the DTM in this study was constructed using the TIN algorithm as the RGB camera’s ability and UAV mission’s setting could not penetrate through the winter pea canopy to get enough data of the bare earth surface to construct DTM via the SfM algorithm. The generated DTM technique in this study requires a clean and sufficient inter-plot area (bare earth surface) to benefit the extracting process of the elevation information for the TIN algorithm.

**Point Cloud-Based Technique for Crop Height Estimation**

In regard to the CH extracted from the point cloud-based technique (Figure 5a), CH at 95% height showed a consistent and high correlation ($r = 0.79 - 0.92$, $p < 0.001$) with measured CH for all datasets. Overall, the correlation coefficient between the two flying altitudes was comparable to the DSM-based CH estimates. Nevertheless, CH extracted from Genesee, and Pullman locations data showed differences between digital traits (e.g., 95H, Max, and Max5H) extracted from point cloud data, which could be the effect of the plot segmentation process to create a noise-free single winter pea plot. This process would affect the extraction of the highest and lowest point cloud position (Figure 3a).

With the inconsistent correlation between data, the vegetation point clouds in this study were generated under the very complex surface (winter pea is an herbaceous legume with angular/roundish hollow stems) and micro relief-height variation. Thus, the off-position point clouds (from the crop characteristic, including sensor and SfM algorithm efficiency) were removed to maintain the shape of the winter pea plot for 3D model reconstruction (Figure 3a). Another potential reason was that the soil subtraction process from the OBIA technique in the study did not wholly remove soil surface point clouds. The technique’s objective was to keep some point clouds of soil surface under/around the plot boundary as a base for reconstructing the 3D model. These factors may have affected the accuracy of CH data, particularly CH that measured from the highest point cloud position and the range between point clouds, as CH was extracted from the position/range of the specific point clouds (Figure 3b). A similar issue also was described in Y. Jiang et al. (2018). The sample selection (usually 3 plants represented within the plot) during standard crop height measurement could also have contributed to the variability.
Figure 5. Relationships between crop height data (at F50 stage) acquired from standard and digital traits extracted from UAV imagery of three locations—Genesee, Garfield, and Pullman (a) correlation coefficients from DSM technique and 3D model technique, and (b) linear regression from DSM-based method of 95th percentile CH. CH: Crop height; DSM technique – Max: Maximum CH; 95P: 95th percentile CH; 90P: 90th percentile CH; 85P: 85th percentile CH; Mean: Average CH; Point cloud technique – Max: CH at maximum height; 95H: CH at 95th percentile height; Max-5H: CH difference between the maximum and 5th percentile height; 95H-5H: CH difference between 95th and 5th percentile height. Significant probability level: * 0.05, ** 0.01, *** 0.001.

Fresh AGBM Estimation

Vegetation Index-Based Technique

Crop volume estimated from the three techniques on UAV imagery at the F50 stage: VI, DSM, and 3D model, as shown in Figure 2a, was related to estimating the fresh AGBM (harvest data). In the VI-based technique, the 90th percentile and mean VI data of 12 VIS that are commonly applied and implied to estimate plant/crop biomass were extracted. One of the major contributors to the VI data is the color pigment (chlorophyll) content on the crop leaves/stems. Thus, the VI data was computed for the crop canopy area of the individual plot to extract VI-based CV data (although represented an area rather than CV, termed as VI-based CV data) that accounted for the amount/area of crop to estimate fresh AGBM (Q. Jiang et al., 2019; Tefera et al., 2022).

The correlation coefficient demonstrated that the 90th percentile and mean of NDRE (Figure 6a) presented a good relationship with the fresh AGBM for all datasets ($r = 0.55 – 0.86$, $p < 0.001$). Amongst the features, 90th percentile and mean Clre and NDRE data showed high correlation with fresh AGBM, especially for Genesee and Garfield datasets ($r = 0.66 – 0.88$, $p < 0.001$) than Pullman dataset ($r = 0.55 – 0.66$, $p < 0.001$). These differences could be associated with the differences in the biomass between the experimental trials (Genesee and Garfield: panel 1921; Pullman: panel 2021cc) as
diverse winter pea genotypes typically have variable growth dynamics and crop morphology/characteristics (Figure 4b). Hence, reflectance responding to the exhibited variation may have resulted in the VI-based CV accuracy as found in Quiros Vargas et al. (2019).

**Figure 6.** Relationships between crop volume data (at F50 stage) acquired from standard and digital traits extracted from UAV imagery of three locations - Genesee, Garfield, and Pullman (a) correlation coefficients from VI technique, DSM technique, 3D model technique, and (b) linear regression from 3D model technique of alpha shape ($\alpha = 1.5$). CV: Crop volume; VI technique – 90P: 90th percentile of VI; Mean: Average VI; 3D model technique – Alpha1.5: Alpha shape ($\alpha = 1.5$); Alpha1.0: Alpha shape ($\alpha = 1.0$); Alpha0.5: Alpha shape ($\alpha = 0.5$); Concave: Concave hull; Convex: Convex hull. Significant probability level: * 0.05, ** 0.01, *** 0.001.
In addition, the correlation coefficient between VI-based CV extracted on a specific area was generally higher than the data extracted from the full plot area to the harvested biomass in all datasets. These results make sense as the digital trait extracted specific area directly related to the harvested biomass. The common VI-based CV presenting the high correlation \((r = 0.60 - 0.88, p < 0.001)\) in this specific area for three locations data were 90th percentile and mean CIre and NDRE. Other VI-based CV in this specific area: EVI2, MCARI2, MTVI2, NDVI, and OSAVI of 90th percentile and mean also showed a good relation with fresh AGBM \((r = \sim 0.60 - 0.80, p < 0.001)\). To summarize of VI-based CV technique, CIre and NDRE, both red-edge spectrum-based vegetation indices, had a better performance than other VIs for fresh AGBM estimation used in this study. Other studies have also found that the red edge-based indices have a significant relationship with plant/crop biomass due as this spectrum is sensitive to chlorophyll absorption (Gitelson et al., 2003; Kanke et al., 2016; Cheng et al., 2017; Q. Jiang et al., 2019; Banerjee et al., 2020; Tefera et al., 2022).

**DSM-Based Technique**

Crop volume for each plot from the DSM-based technique was computed by multiplying the CH with the canopy coverage area, both estimated from CSM. The CVs were significantly correlated with fresh AGBM \((r = 0.57 - 0.86, p < 0.001)\), as shown in Figure 6a. Between experiments, the correlation coefficients were higher \((r = 0.71 - 0.86, p < 0.001)\) between CV and AGBM in Genesee and Garfield (2019) than that of Pullman \((r = 0.57 - 0.64, p < 0.001)\), similar to the results from the VI-based CV approach. In addition, the produced fresh biomass of entries in Pullman was much higher the same plot area (Figure 4b). Thus, the canopy biomass outside the segmented plot area (resulting from lodging and excessive biomass) may have been missed during data extraction.

The correlation coefficient in the specific area also showed a slightly better relationship than the results from the full plot area, similar to the VI-based CV approach, which could be the direct relationship between area and harvested biomass. In regard to flying altitudes, the results were not significantly different as reported in other studies (Peña et al., 2015; Jin et al., 2017). This could be associated with the speed of UAV during data acquisition. A low speed (2 m/s) would translate to capturing high-quality images with high overlap to provide a better position/distance of object accuracy. Therefore, the UAV’s flight mission parameters, such as the altitude, speed, and overlap, are together vital for high-quality data collection, which should be set to balance out between spatial resolution and spectral discrimination to achieve the objective of data accuracy (Gómez-Candón et al., 2014; Mesas-Carrascosa et al., 2015).

**3D Model-Based Technique**

RGB point clouds were utilized to reconstruct three types of 3D models to estimate the fresh AGBM (Figure 3b) and compared to the standard approach’s data. In general, the correlation coefficient showed that alpha shape \((\alpha = 1.5)\) based volume had a better relationship and provided a consistent correlation with the fresh AGBM than other 3D models \((r = 0.78 - 0.81, p < 0.001)\) for the three locations and both flying altitudes (Figure 6a). With the correlation performance, linear regression of three trial locations on alpha shape \((\alpha = 1.5)\) based volume data was conducted using the 20 m flying altitude results (Figure 6b). A moderate estimator was found \((R^2 = 0.61 – 0.65, \text{RMSE} = 0.13 – 0.39 \text{kg/m}^2)\) from three locations suggesting an acceptable accuracy and repeatability of fresh AGBM estimates.

In terms of 3D model approach, both alpha shape \((\alpha = 1.5)\) and convex hull volume demonstrated a higher correlation \((r = 0.79 – 0.81, p < 0.001)\) with the fresh AGBM in 2019 trials than 2020 trial \((r = 0.66 – 0.78, p < 0.001)\). The convex hull is the smallest convex closure containing all the given points, where the method accounts for the unoccupied space inside the closure to calculate a volume. Thus, the large portion of unoccupied space in the convex hull provided a lower relationship with the fresh AGBM in the 2020 trial (Pullman) because the crop was taller and had a different morphological status. In contrast, the convex hull volume of trials in 2019 (Garfield and Genesee) related to the fresh AGBM as the crop was flat (shorter), reasoning to a small gap of unoccupied space (Y. Jiang et al., 2019; Di Gennaro and Matese 2020). Due to this reason, the alpha shape \((\alpha = 1.5)\) volume may have a better relationship with the fresh AGBM in 2020 trail as the alpha shape is a generalized convex hull method, which allows the adjustment of the constant – alpha value \((\alpha)\) which allows the user to optimize/tune the tightness the shape around the model.

In this study, the RGB images to construct point clouds were collected from a single grid with 80% front and 70% side overlap at camera inclinations of 90\(^\circ\) of UAV mission. Nevertheless, the point cloud numbers and the accuracy of point cloud position can further be improved by using a double grid pattern, different camera inclinations, and an increased percentage of image overlap (Kothawade et al., 2021; Kuželka et al., 2020; Moreira et al., 2021).

**Dry AGBM Estimation**

UAV imagery at the PM stage was processed using two techniques, DSM and 3D model, to extract CV and relate it with the dry AGBM (harvested biomass acquired during physiological maturity). Figure 7a shows that CV from the DSM-based technique had a moderate relationship \((r = 0.44 – 0.85, p < 0.001)\) for trials in 2019, but very poor results for 2020 trail. The winter pea at the Pullman location significantly grew over the plot boundary, as shown in Figure 8, which could have been a potential reason. A significant lodging was also observed in the Genesee dataset. Nevertheless, CV from 3D model-based approach with the alpha shape \((\alpha = 1.5)\) volume provided a consistent and high correlation coefficient \((r = 0.70 – 0.81, p < 0.001)\).
0.001) with dry AGBM over other 3D models from all datasets (Figure 7a). With the consistency correlation of the alpha shape ($\alpha = 1.5$) volume, linear regression was also performed from the data at 20 m flying altitude, which provided the moderate estimator ($R^2 = 0.48 – 0.66$, RMSE = 0.02 – 0.06 kg/m²) of this 3D reconstruction model, as demonstrated in Figure 7b.

Figure 7. Relationships between crop volume data (at PM stage) acquired from standard and digital traits extracted from UAV imagery of three locations - Genesee, Garfield, and Pullman (a) correlation coefficients from VI technique, DSM technique, 3D model technique, and (b) linear regression from 3D model technique of alpha shape ($\alpha = 1.5$). Significant probability level: * 0.05, ** 0.01, *** 0.001.

Figure 8. Part of CHM model at the PM stage with plot segmentation polygon (red color) for CH and crop coverage area extraction.
Summary and Conclusion

Overall, both DSM and point cloud data could be utilized to estimate crop height. However, at the same data collection settings of 20 m UAV’s flight altitude and similar CH extraction area, the DSM technique was the better option for CH estimation as this technique provided high and stable correlation results with ground reference data. Alternatively, all three-based approaches (VI, DSM, 3D model) demonstrated the feasibility of using the UAV integrated with RGB or multispectral camera to measure AGBM, especially fresh AGBM. Between these approaches, the point cloud data generated from RGB images collected at 20 m flying altitude with the 3D model technique—alpha shape with $\alpha = 1.5$—provided the high and consistent correlation results across different locations and experiments on both fresh and dry AGBM but, the processing of such datasets was complex. The VI and DSM-based approaches, nonetheless, also show a high correlation, but the implementation of these approaches should be considered based on the type and characteristic of the plant/crop. In terms of precision and accuracy, both digital traits in the study presented a higher correlation when extracted from a similar area as that of the standard measurement (crop height and harvested AGBM).

Regarding the point clouds to reconstruct 3D models, the number and precision of point clouds from UAV-RGB imagery might be lower than those generated from the LiDAR system; however, UAV-RGB imagery is an inexpensive and rapid solution compared to the LiDAR system. Furthermore, the point cloud quality from UAV-RGB imagery can be adjusted or improved by optimizing the UAV flight mission parameters as described above (Rogers et al., 2020). In addition, various software/programs to process point clouds from UAV-RGB imagery are open-source software—for example, OpenDroneMap for constructing point clouds and DSM from RGB imagery (https://www.opendronemap.org/; accessed on Jan 5, 2022). Other software solutions are available to visualize and manipulate the point clouds, such as QGIS (starting from version 3.18) and CloudCompare, including Python’s library like WhiteboxTools, and Open3D (http://www.open3d.org/; accessed on Jan 5, 2022). These resources may significantly improve the opportunities and benefit the research community to use point clouds from UAV-RGB imagery.

In summary, these results offer a resource-efficient, non-destructive approach to breeders/researchers and growers in estimating AGBM as often manual or machine harvest is a tedious and labor-intensive activity. Further work will focus on data analysis, as many studies have applied multivariate traits to increase the accuracy in predicting biomass yield (Tilly et al., 2015; Q. Jiang et al., 2019; Banerjee et al., 2020; Tefera et al., 2022). Thus, the multivariate traits to predict biomass yield will be explored in future studies, including environmental factors that explain the interactions between genotype, environment, and management ($G \times E \times M$) to provide informed decisions in the breeding programs.

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