The relationship between vegetation indices derived from UAV imagery and maturity class in potato breeding trials

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Abstract

In potato breeding, maturity class (MC) is a crucial selection criterion because this is a critical aspect of commercial potato production. Currently, the classification of potato genotypes into MCs is done visually, which is time- and labor-consuming. Unmanned aerial vehicles (UAVs) equipped with sensors can acquire images with high spatial and temporal resolution. The objectives of this study were to 1) establish the relationship between vegetation indices (VIs) derived from UAV imagery at three potato growth stages and visually estimated maturity class and 2) determine if multiple in-season evaluations of VIs variation within breeding trials could be helpful in potato genotype selection.

Research was conducted in 2023 on regular Potato (Solanum tuberosum L.) breeding trials of the Zamarte Potato Breeding Ltd. company at Zamarte in northern Poland. The trials covered plots with potato A and B-clones representing the breeding program's second and third field generation/propagation, respectively. The relationships between VIs (OSAVI – Optimized Soil Adjusted Vegetation Index, GOSAVI – Green Optimized Soil Adjusted Vegetation Index, NDRE – Normalized Difference Red Edge, and NDVI – Normalized Difference Vegetation Index) derived from UAV imagery (UAV, Phantom 4 Multispectral, DJI, Shenzhen Dajiang Baiwang Technology Co., Ltd., China), obtained three times across vegetation season, and visual potato canopy status (on a 9-degree scale) were determined. Results show that VIs derived from UAV images can be effectively used to remotely assign MCs to potato breeding lines, with similar accuracy for the potato A and B-clones. Among the tested VIs, the NDRE allowed for potato MC evaluation with the lowest mean absolute error (MAE) of 0.79 and 0.81 for the potato A and B-clones, respectively. Multiple in-season evaluations of VIs variation within breeding trials could help to track the potato development and relate this to the MC. Incorporating information on the missing and flowering potato plants in the remote evaluation and including machine learning-derived classification of RGB imagery, may improve the remote MC determination.

Keywords. *potato breeding, crop phenomics, maturity class, digital agriculture, unmanned aerial vehicle, UAV, imagery, vegetation index*

Introduction

In potato breeding, maturity class (MC) is a crucial selection criterion because this is a critical aspect of commercial potato production. Maturity is a complex phenomenon affected by many potato growth and development components (Khan et al., 2013). Currently, the classification of potato genotypes into MCs is done visually, which is time- and labor-consuming. Unmanned aerial vehicles (UAVs) equipped with sensors can acquire images with high spatial and temporal resolution (Koh et al., 2019). The imagery is used to detect and quantify variations in crop color, which is also taken into account in the visual MC evaluation. The UAV imagery can cover the whole experimental area and, in a short time, can get a snapshot of all the plots without changes in the environmental conditions (Li et al., 2014). The high temporal frequency of data collection with UAVs allows for timely estimation of the essential plant traits rather than missing the critical stages in plant development (Burkart et al., 2018). This approach reduces input costs, saves time, and minimizes errors caused by multiple rounds of phenotyping done by various people when evaluating the same plots (Chawade et al., 2019). Recent studies have demonstrated UAV platforms' capability to estimate potato plant count using RGB imagery (Sankaran et al., 2017). The image analysis process is more straightforward for potato plants, typically represented as individual objects following image segmentation. The study by Khan et al. (2013) focused on developing a physiological approach to assessing maturity type during the whole course of potato plant development. The researchers concluded that the physiological maturity type criteria explained maturity type in potato more clearly and were better capable of predicting the maturity type of genotypes across diverse environments than the conventional criterion. Nevertheless, those physiological maturity type criteria require physiological measurements to be acquired, which does not reduce the labor requirements. However, there are still gaps in the literature regarding the application of VIs derived from multiple UAV orthomosaics for the estimation of potato canopy variation in breeding trials.

The objectives of this study were to 1) establish the relationship between vegetation indices (VIs) derived from UAV imagery at three potato growth stages and visually estimated maturity class and 2) determine if multiple in-season evaluations of VIs variation within breeding trials could be helpful in potato genotype selection.

Materials and Methods

Location and cultural practices

The research was conducted in 2023 on regular Potato (*Solanum tuberosum* L.) breeding trials of the Zamarte Potato Breeding Ltd. company at Zamarte in northern Poland (53°35'29.87"N,17°30'4.10"E, elevation: 147 m). The trials covered 4480 plots with potato A-clones (breeding lines A – second field generation/preparation) – the earlier stage of the breeding program, and 1330 plots with potato B-clones (breeding lines B – third field generation/preparation) – the later stage of the breeding program. Standard varieties with well-known (in brackets) MC, namely Bielik (1), Longina (3), Gala (3), Oberon (5), Madeleine (5), Impresja (1), and Ismena (3), were planted every ten plots in the A-Clones trial. The varieties Werbena (1), Bielik, Longina, Ismena, Oberon, Gala, Madeleine, and Widawa (5) were planted every five plots in the B-Clones trial. These standard varieties were planted to benchmark the effects of MC among known genotypes.

Visual maturity class observations

The visual MC estimation was done by an experienced breeder during intensive yellowing and bending of potato vines over the beds of very early standard varieties on a 9-degree scale on July 25 and 26, 2023. During the evaluation, the breeder takes into account plant growth habits, uniformity of growth, and intrinsic vine color. Numbers 1 and 9 refer to very early and late genotypes, respectively. The MCs of the potato A and B-clones tested in 2023 in the Zamarte Potato Breeding Ltd. breeding trials ranged from 1 to 8. Very early A-clones, with a completely dry canopy during the visual estimation, were additionally assigned an MC of 0.5. In total, 3529 potato A-clones and 873 potato B-clones were assigned the MC and used for statistical analysis. Each plot consisted of one row (bed) of 6 plants and two rows of 10 plants each for the A- and B-clones, respectively.

UAV image acquisition and processing

The UAV imagery was collected using a Phantom 4 Multispectral (DJI, Shenzhen Dajiang Baiwang Technology Co., Ltd., China) equipped with an FC6360 sensor. The imaging sensor included an RGB camera and multispectral camera array of the following bands: blue (B) – 450 nm ± 16 nm, green (G) 560 nm ± 16 nm, red (R) – 650 nm ± 16 nm, red edge (RE) – 730 nm ± 16 nm, and near-infrared (NIR) – 840 nm ± 26 nm. Flights were conducted with an 80% front and side overlap at 20 m above ground level, resulting in a spatial resolution of 1.1 cm pixel^{-1}. The flight paths were perpendicular to sunlight direction and close to solar noon on cloud-free days to avoid changing light conditions. The flights were coordinated to occur on the same days as the visual MC evaluation, on May 31 (potato growth stage in the range of BBCH 1 to 29), June 26 (potato growth stage in the range of BBCH from 59 to 69, bud development to flowering, respectively), and July 25 and 26, 2021 (Hack et al., 2001). At the last measurement date, the latest potato genotypes were at the end of flowering, but the earliest genotypes were yellowing. The multispectral images were uploaded to the Pix4Dfields computer software (Pix4D S.A. Prilly, Switzerland) for processing and generating orthorectified reflectance maps. Five reflectance maps were generated, one for each spectral band (blue, green, red, red-edge, and NIR). To compensate for soil background influences, the GOSAVI and OSAVI were used (Rondeaux et al. 1996; Sripada et al. 2005). Additionally, NDVI and NDRE, commonly used for monitoring crop canopy but not requiring sophisticated calculations, were also applied (Rouse et al. 1974; Barnes et al. 2000). Using QGIS.org (2022), a rectangular region of interest (ROI), in the form of a shape file, of 0.60 (width) by 2.04 m, and 1.2 (width) by 3.40 m, for each of the plots of the A-clones and B-clones, respectively, was created and manually placed over the potato plots. A function of zonal statistics in QGIS was used to derive VIs values for single potato plots from raster layers of the VIs.

Statistical analysis

Relationships between VIs and MC were analyzed using linear regression (R^2) and Pearson's correlation coefficient (r) in Microsoft® Excel (Microsoft Corporation, Redmond, Washington, United States). Correlations at α=0.05 were considered significant. Mean absolute error (MAE) was estimated for the VI showing the highest correlation with MC. The percent coefficient of variation (CV) was used to measure the variations of VI values within the potato trials.

Results and discussion

Variation of growth stage and vegetation indices values within the potato A and B-clone trials

At the first measurement date, potato genotypes in both A and B-clones trials showed the highest growth stage variation, namely from the very beginning of germination (BBCH of 0-9) to shoot development (BBCH of 21-29). Therefore, at the same time, the variation of all tested VIs was also the highest (Fig. 1a and 1b).

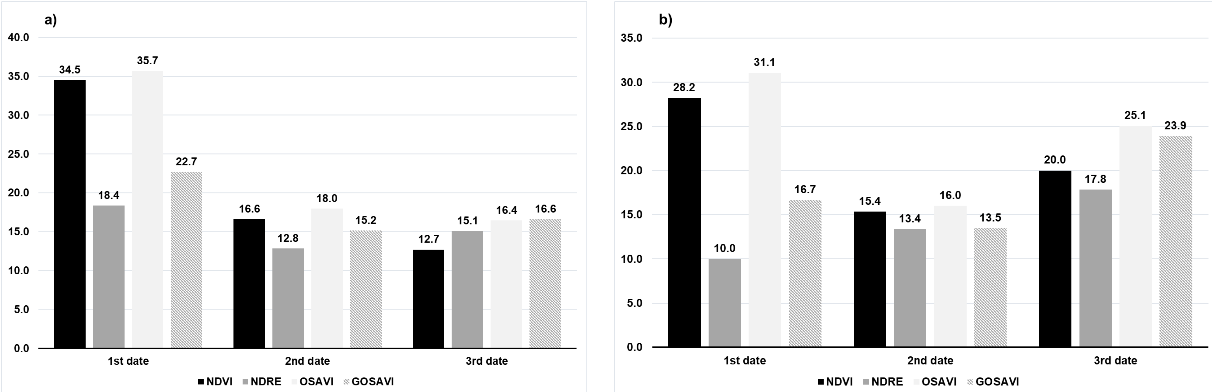
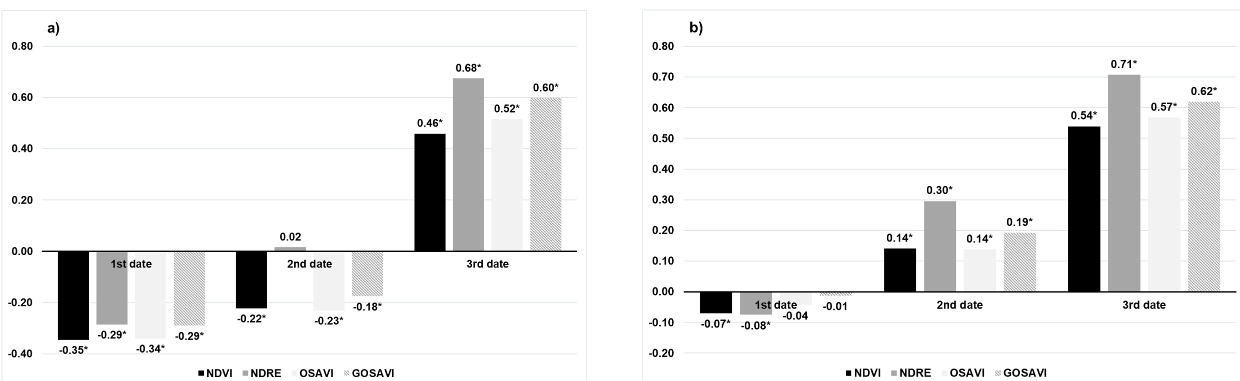


Fig. 1. The coefficient of variation (%) of vegetation indices values within the potato a) A-clones and b) B-clones trials at three measurement dates.

The second and third measurement dates observed a much lower variation of the potato growth stage, which was reflected by the lower variation of the VIs during these measurements. Among all the VIs tested in both potato trials, NDRE showed the lowest variation during all measurement dates. This observation means that NDRE is more useful for the remote evaluation of the potato MC because a smaller number of differently-looking plots is assigned to the same MC.

Relationship between the maturity class and vegetation index values for potato A and B-clones

At the first measurement date, all tested VI showed a significant, negative correlation with the MC estimated two months later (figures 2a and 2b). This could be explained by the fact that the earliest developing potato genotypes (with high VI values during the first measurement date) consequently earlier showed symptoms of senescence and were assigned a lower MC by the breeder. The same tendency was also observed in the B-clones trial during the second measurement date. Among the tested VIs at the third measurement date, the NDRE showed the highest correlation with MC, *r* value of 0.68 and 0.71, in potato A- and B-clones, respectively.



* – a critical value of r=0.033 at α=0.05; n=3529

* – a critical value of r=0.066 at α=0.05; n=873

Fig. 2. The correlation coefficient (r) values (a) for the relationship between the maturity class and vegetation indices values; for a) potato A-clones and b) potato B-clones.

The MAE of the maturity class of potato A- and B-clones, predicted based on NDRE values

The mean absolute error for predicting MC was presented only for NDRE since this VI showed the strongest relationship with MC. The MAE values were 0.79 and 0.81 for the potato A and B-clones, respectively (figures 3a and 3b), and they indicate that, on average, MC could have been evaluated in both potato trials with similar errors.

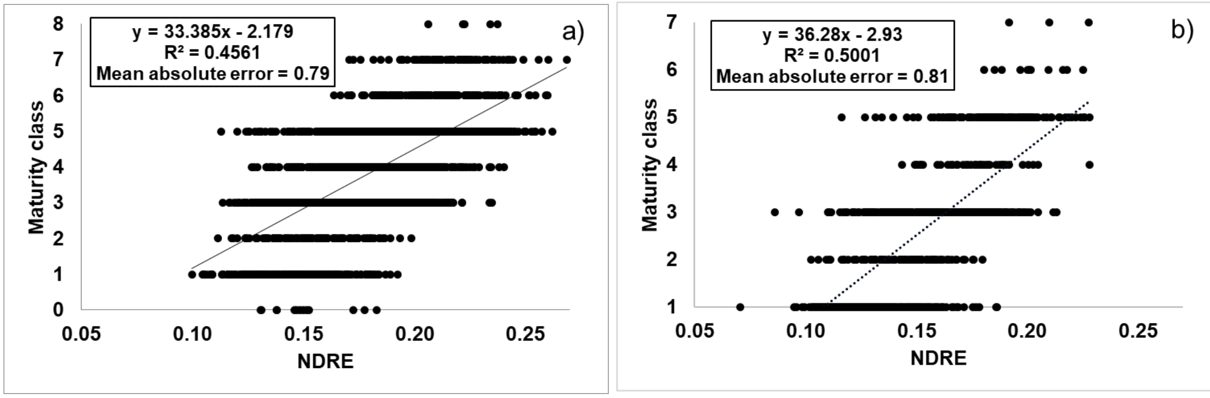


Fig. 3. A scatter plot of NDRE values versus maturity class for (a) potato A-clones and (b) potato B-clones, including MAE and R^2 values.

In the case of 69.7% of the genotypes in potato A-clones and 68.6% of the genotypes in B-clones, MC was evaluated using NDRE with an absolute residual value of 1 or less (data not shown).

Limitations of maturity class evaluation using vegetation indices

A closer investigation of the appearance of the potato crops on the RGB images, registered by the UAV camera, characterized by the highest absolute residual value of the predicted MC, indicates that missing plants decreased the values of the tested VIs. Still, at the same time, the left plants were sufficient to assign a relatively high MC by the potato breeder (figure 4a). The flowering of potato plants (figure 4b) as a sign of late maturity was incorporated in the breeder's MC evaluation but not taken into account while calculating the NDRE.

Fig. 4. Appearance of potato crops on example plots of the potato B-clones with under-estimated MC using NDRE due to a) missing plants and b) flowering plants taken into account during visual MC evaluation by the breeder but undetected by UAV imagery.

Summary

Early evaluation of potato breeding trials with UAV imagery could be useful for the determination of potato germination and used for preliminary indication of genotypes MC. Namely, the earliest developing genotypes in the potato A-clones trial showed a significant, negative correlation with MC. Moreover, results show that VIs derived from UAV images can be effectively used to remotely assign MCs to potato breeding lines, with similar accuracy for the potato A and B-clones. Among the tested VIs, the NDRE allowed for potato MC evaluation with the MAE of 0.79 and 0.81 for the potato A and B-clones, respectively. The accuracy of potato MC estimation using UAV image-based methods may be improved by including information on the missing and flowering potato plants and incorporating machine learning-derived image classification.

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