Am. J. Potato Res. (2017) 94:658–663
DOI 10.1007/s12230-017-9604-2

SHORT COMMUNICATION

High-Resolution Aerial Imaging Based Estimation of Crop Emergence in Potatoes

Sindhuja Sankaran[1] **· Juan José Quirós**[1,2] **· N. Richard Knowles**[3] **· Lisa O. Knowles**[3]

Published online: 15 September 2017

Abstract Plant emergence and stand establishment are key indicators of early crop development that are routinely assessed in potato agronomy and crop improvement research. The standard method for evaluating emergence is through manual plant counts at regular intervals. In this proof-of-concept study, unmanned aerial vehicles integrated with multispectral imaging were used for high-throughput evaluation of crop emergence under field conditions. High-resolution aerial imaging was performed at 15 m above ground level to capture data from potato plots of two varieties ('Alturas' and 'Payette Russet') in which the seed had been treated with different concentrations of growth regulators (including non-treated controls). The treatments resulted in differences in plant emergence and establishment. The images were collected at 32, 37, and 43 days after planting (DAP). Image-based features such as plant count, SUM-NDVI, and SUM-BINARY were computed from normalized difference vegetation index (NDVI) images for each treatment plot using ArcGIS®. The Pearson's correlation coefficients (r) were significant ($p < 0.05$) between image-based plant counts ($r = 0.82$) and SUM-NDVI ($r = 0.62$-0.73) with that of manual plant counts for both varieties, especially at early growth stages (32 DAP) when differences in emergence among treatments were more pronounced. The treatment effects on plant emergence and establishment were effectively resolved in the aerial multispectral images. Selection of the pertinent polygon threshold area to eliminate noise in delineating individual plants during image processing was important for resolution of treatment effects. The data shows that the technique can be applied in potato establishment evaluation.

Resumen La emergencia y el establecimiento de plantas son indicadores clave en el desarrollo temprano de un cultivo, siendo variables comúnmente evaluadas en investigaciones para mejoramiento genético del cultivo de papa. El método normalmente utilizado para evaluar emergencia es el conteo manual de plantas en intervalos regulares. Para evaluar emergencia en condiciones de campo, en este "estudio de prueba de concepto", se utilizó un sistema de alto rendimiento constado por una aeronave remotamente piloteada con una cámara multiespectral integrada. Se tomó imágenes de alta resolución a 15 m de altura para capturar datos de parcelas de dos variedades de papa ("Alturas" y "Payette Russet"), cuyas semillas fueron tratadas con diferentes concentraciones de reguladores de crecimiento (incluyendo también testigos sin tratamiento). Los tratamientos mostraron diferencias en emergencia y establecimiento de plantas. Se colectó imágenes a 32, 37, y 43 días después de la siembra (DDS). Se utilizó el programa ArcGIS® para obtener el NDVI (índice de vegetación de diferencia normalizada) de cada parcela, a partir del cual se obtuvo el número de plantas, SUM-NDVI y SUM-BINARY. Se encontró correlación significativa ($p < 0.05$) entre el conteo de plantas basado en imágenes ($r = 0.82$) y en SUM-NDVI ($r = 0.62$-0.73), con respecto al conteo manual para ambas variedades, especialmente en los estadios tempranos de crecimiento (32 DDS), cuando

Sindhuja Sankaran and Juan José Quirós are equal contributing authors.

✉ Sindhuja Sankaran
sindhuja.sankaran@wsu.edu

[1] Department of Biological Systems Engineering, Washington State University, Pullman, WA 99164, USA

[2] Departamento de Engenharia de Biossistemas, Escola Superior de Agricultura Luiz de Queiroz, ESALQ, Universidade de São Paulo, Piracicaba, SP 13418-900, Brazil

[3] Department of Horticulture, Washington State University, Pullman, WA 99164, USA

las diferencias en emergencia entre tratamientos eran más pronunciadas. Los efectos del tratamiento en emergencia y establecimiento fueron efectivamente detectados con las imágenes aéreas multiespectrales. Fue importante seleccionar adecuadamente el área de los polígonos utilizados para disminuir el ruido delimitando las zonas cubiertas por el cultivo. Los datos muestran que la metodología presentada se puede aplicar en la evaluación del establecimiento del cultivo de papa.

Keywords Remote sensing · Unmanned aerial vehicle · Normalized difference vegetation index · Image processing · Plant growth

Introduction

In recent years, the availability of different types of unmanned aerial vehicles (UAVs) and simple multispectral cameras have spurred several new applications in agriculture. Validation of remote sensing technology to assess vegetation has been reported previously (Bouman et al. 1992; Carlson and Ripley 1997; Serrano et al. 2000; Vina et al. 2004). Most recently, Zhou et al. (2016) evaluated the effect of crop hail damage on potato canopy utilizing UAV-based multispectral aerial imaging and vegetation indices, such as normalized difference vegetation index (NDVI) and green normalized vegetation index (GNDVI). They demonstrated that aerial imaging within 10 days of damage was critical to accurately capture the intensity of hail damage. Similarly, Sugiura et al. (2016) evaluated late blight symptoms to assess disease severity using RGB imaging from an UAV in comparison to visual disease ratings. The disease severity was estimated from images by computing the ratio between the damaged and healthy areas. Thresholding was performed to determine whether the image pixels were healthy or diseased. A strong consensus between ground truth (visual rating) and image data was observed when disease severity ratings were compared. Their study revealed good potential for using UAV-based imaging in estimating disease severity.

The application of UAV-based technology in potato production is emergent and further studies are required to phenotype different crop traits to advance the use of sensor technology for research, breeding, and precision agriculture (Midmore 1984; Maris 1988). In particular, the estimation of plant emergence and establishment in potato with these devices has not been documented. Numerous factors can affect the emergence response of potato including variety, seed-tuber physiological age, soil temperature, disease, and various seed treatments that affect apical dominance (stem numbers) and dormancy break (e.g. plant growth regulators) (Eshel and Teper-Bamnolker 2012; Knowles and Knowles 2016). The standard method for assessing effects of management and variety on emergence of potato is to visually count the number of plants emerged at frequent intervals during the establishment phase of development (Knowles and Knowles 2006; Blauer et al. 2013; Herman et al. 2016). A high-throughput sensing technique can greatly enhance the efficiency in emergence evaluation. Therefore, the overall objective of this study was to compare the utility and accuracy of UAVs and multispectral imaging with manual plant counts for assessing potato crop emergence.

Materials and Methods

Field Plots and Emergence Assessment

Seed tubers of 'Alturas' and 'Payette Russet' were cut and treated with five combinations and concentrations of plant growth regulators designed to accelerate or delay plant emergence relative to the non-treated seed. These treatments are part of a larger unrelated multi-year project, which will be described in a future publication. The 2015 plots from this ongoing project served for validation of the efficacy of remote sensing of emergence in the study reported herein. The identity of the growth regulator treatments are not relevant to the objectives of the present study and are therefore not divulged to avoid conclusions about their potential efficacy based on 1 year of data. The treatments are hereafter designated as 1-6 (Treatment 1 was control, without any seed treatment).

The treated seed tubers were planted in field plots in a randomized complete block design (5 replicates of 24 seed pieces per treatment) at the Washington State University Research Unit, Othello, WA (46° 47.277′ N. Lat., 119° 2.680′ W. Long.) on April 13, 2015, as described by Herman et al. (2016). Rows were spaced 86 cm apart. Individual treatment rows were flanked by non-treated guard rows. The seed pieces were planted 25 cm apart within one treatment row. Plant emergence was recorded at 32, 37, and 43 days after planting by counting the number of plants emerged in each plot. These plant counts constituted the ground-reference emergence data, which was subsequently compared with data from the UAV flights.

UAV Data Acquisition

Aerial images were acquired using an octocopter ARF OktoXL 6S12 (HiSystems GmbH, Moormerland, Germany) powered by a lithium-ion polymer battery with a potential 2.5 kg payload and equipped with the following sensors: gyroscope, accelerometer, compass, global positioning system receiver, and pressure sensor. Way-point Global Positioning System (GPS) navigation was applied to capture the images using a radio transmitter (MX20 Hott, Graupner, Stuttgart, Germany) with a 4 km range. The waypoint GPS navigation facilitates operating the UAV in an automated fashion by loading and configuring pre-planned points within the region of interest (area that covers all the treatment plots). Factors such as imaging altitude, image capture frequency, speed of flight, and hovering time at each pre-planned point were defined for each flight. The UAV platform carried a gimbal with a modified multispectral digital camera, Canon Powershot ELPH 340 HS (LDC LLC, Carlstadt, NJ), which has channels for red (R), green (G), and near infrared (NIR) bands. The system was programmed to automatically capture 8-bit JPG images (16 megapixels; 4608 × 3456) every 5 s. Reference boards and flags between treatment plots were incorporated for ease in block and plot segmentation on the images, respectively. This was important as the treatment plots in adjacent rows did not start and end at the same position (Fig. 1a). The images were captured at 32, 37, and 43 days after planting (DAP) at 15 m above ground level under sunny conditions. A reference

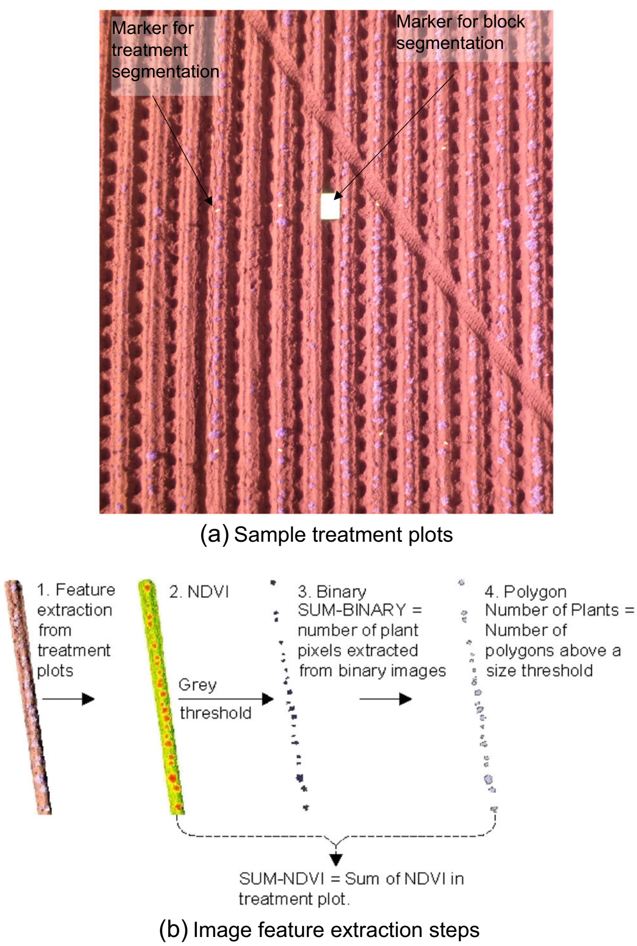


Fig. 1 Data processing method for extraction of the image features for individual treatment plots. **a** Sample treatment plot showing markers for treatment and block segmentation (dark areas in the furrows between hilled rows are pits made by the dammer diker), and **b** Image feature extraction steps utilized to extract image-based data (number of plants, SUM-NDVI, and SUM-BINARY)

panel (25 × 25 cm, Spectralon Reflectance Target, CSTM-SRT-99-100, Spectra Vista Cooperation, NY) was placed in the field to correct for changing light conditions.

Image Analysis

Images were processed using the raster calculator and zonal statistics tools of ArcGIS (10.2, ESRI, Redlands, CA). Raster refers to a matrix/grid of pixels in a grid, which is represented by a data value. The multispectral imaging generates a digital number (DN = 0 to 255, 8-bit, 0 representing no reflectance and 255 representing maximum reflectance) representing reflectance in the R, G, and NIR region. Radiometric correction was then performed using the Spectralon reference panel. After radiometric corrections of images, the steps followed were as described and illustrated in Fig. 1b.

During image processing, the first step was to extract the treatment plots in the original raster. With the segmented images representing each plot, normalized difference vegetation index (NDVI, Rouse et al. 1974) image was generated using Eq. 1:

$$NDVI = \frac{R_{NIR} - R_R}{R_{NIR} + R_R} \tag{1}$$

where R_{NIR} and R_R refers to reflectance (DN) at NIR and R spectral bands. From the NDVI image, summation of all the pixels (SUM-NDVI) for each plot was computed. These data represent the sum of canopy NDVI (includes all new and old leaves, and small and large plants) in a treatment plot. A threshold (82% of the maximum value of the NDVI for a given day and variety) was then applied to convert the NDVI image into a binary image. In this case, the new and old leaves were converted into a single value. The total number of binary pixels was defined as SUM-BINARY. This data represents the canopy coverage area for each treatment plot. Finally, the binary image was converted into a vector file of polygons (objects), where each polygon over a size threshold (100 cm^2) was defined as one plant. The total plant count using images was then estimated.

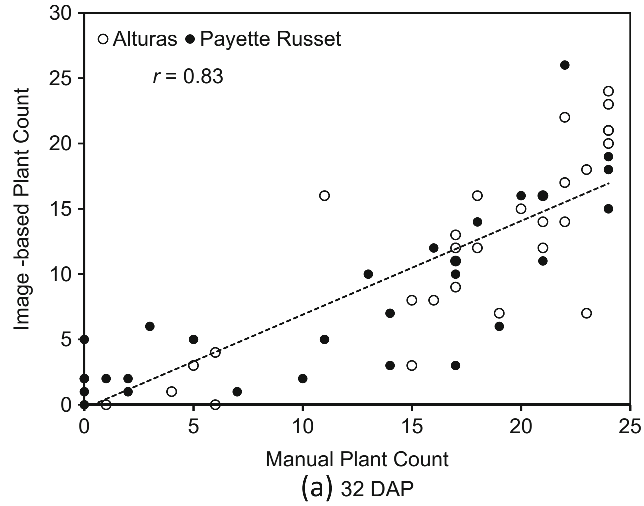
Statistical Analysis

The image-based data (plant count, SUM-NDVI, SUM-BINARY) were correlated with the ground reference plant count data at each time and for each variety. Pearson correlation coefficients (r) and the probability values (p) were calculated. The correlation was performed on plant count data (manual and image-based) acquired from each replicate of each treatment (6 treatments × 5 replicates = 30 plots). Statistical analysis was performed using SAS® (ver. 9.2, SAS Institute, Cary, NC, USA).

Results and Discussion

The three image-based emergence features, plant count, SUM-NDVI, and SUM-BINARY, were correlated with manual plant counts (30 data points). Correlation coefficients and p-levels are reported in Table 1. In general, all correlation coefficients, except for manual and image-based plant counts at 37 DAP for 'Alturas', were significant. The low correlation (r = 0.24) between image-based and manual count data for 'Alturas' was due to its shorter dormancy (Novy et al. 2003, 2016), which resulted in higher emergence relative to 'Payette Russet' by 37 DAP (as seen in Fig. 2). In contrast to 'Alturas', all correlations for emergence of 'Payette Russet' were high and significant at both 32 and 37 DAP (Table 1). The combined data of the two varieties also gave good results with correlation coefficients of 0.83 (p < 0.0001) for the image-based versus manual count data at 32 and 37 DAP (Table 1, Fig. 2). It was not possible to compute the number of plants using remotely sensed images at 43 DAP, as both varieties had achieved full emergence and within-row canopy closure by this time. These results underscore one of the limitations of the remote sensing technique for assessment of plant emergence and establishment. In the latter stages of plant establishment when plant canopies begin to overlap, the resolution of individual plants by remote sensing decreases. Nevertheless, visualization through remotely sensed images offers an alternative method for assessing early plant emergence and stand establishment that circumvents the challenges and difficulties of navigating the hills, furrows, and dammer diker pits of research plots and/or large-scale commercial fields to manually acquire plant count data.

SUM-NDVI data represents the total canopy NDVI that includes all plant pixels, with low and high vigor plants defined as having low and high NDVI values, respectively.



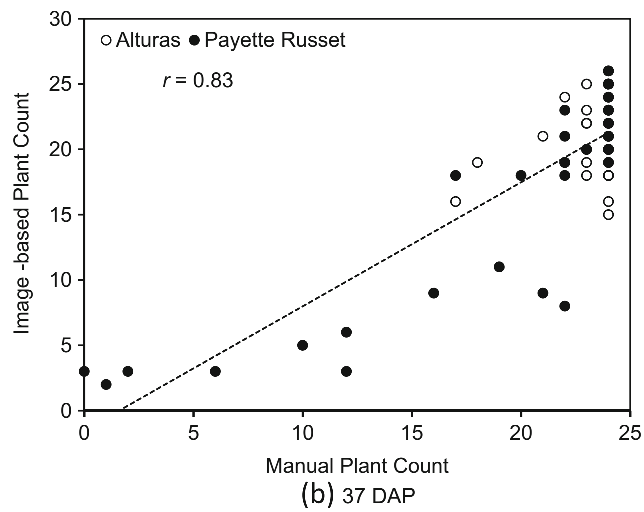


Fig. 2 Correlation between manual and image-based plant count data (both varieties combined) at **a** 32 days after planting (DAP) and **b** 37 DAP

Table 1 Correlation analysis results between the manual plant count measure with respect to remote sensing data (plant count, SUM-NDVI, and SUM-BINARY)

Days after planting (DAP)	Image-based plant count		SUM-NDVI		SUM-BINARY	
	r	p	r	p	r	p
'Alturas'						
32	0.82	<0.0001	0.73	<0.0001	0.71	<0.0001
37	0.24*	0.2115	0.57	0.0010	0.17*	0.3660
43	-	-	0.38	0.0364	0.45	0.0119
'Payette Russet'						
32	0.82	<0.0001	0.62	0.0003	0.58	0.0008
37	0.87	<0.0001	0.72	<0.0001	0.66	<0.0001
43	-	-	0.53	0.0029	0.21*	0.2624
Combining both varieties						
32	0.83	<0.0001	0.68	<0.0001	0.65	<0.0001
37	0.83	<0.0001	0.61	<0.0001	0.18*	0.1640
43	-	-	0.42	0.0009	0.22*	0.0849

r correlation coefficient, p probability, *Not significant at α = 0.05

SUM-BINARY normalized the plants as 0 or 1 and computed the total number of all plant pixels independent of vigor. Interestingly, SUM-NDVI showed better correlations than SUM-BINARY values.

In addition to a good correlation, the image-based features resolved the treatment effects on plant emergence as observed from Fig. 3. On average, the image-based counts were lower than the manually obtained plant counts, which could be due to a conservative selection of polygon threshold. When the threshold was modified, the count increased by 1-2 plants and did not change the correlations significantly. It is therefore important that an optimum polygon threshold be selected for counting the number of plants. A broader threshold will increase the chances of two plants being counted as one, leading to lower image-based plant counts. At the other extreme, a polygon threshold too narrow can count noise in the images as a plant, thereby increasing the plant count greater than ground-truth values. Nevertheless, given the plant growth differences with emergence of new plants and establishment of emerged plants, the image-based features captured the treatment effects on emergence.

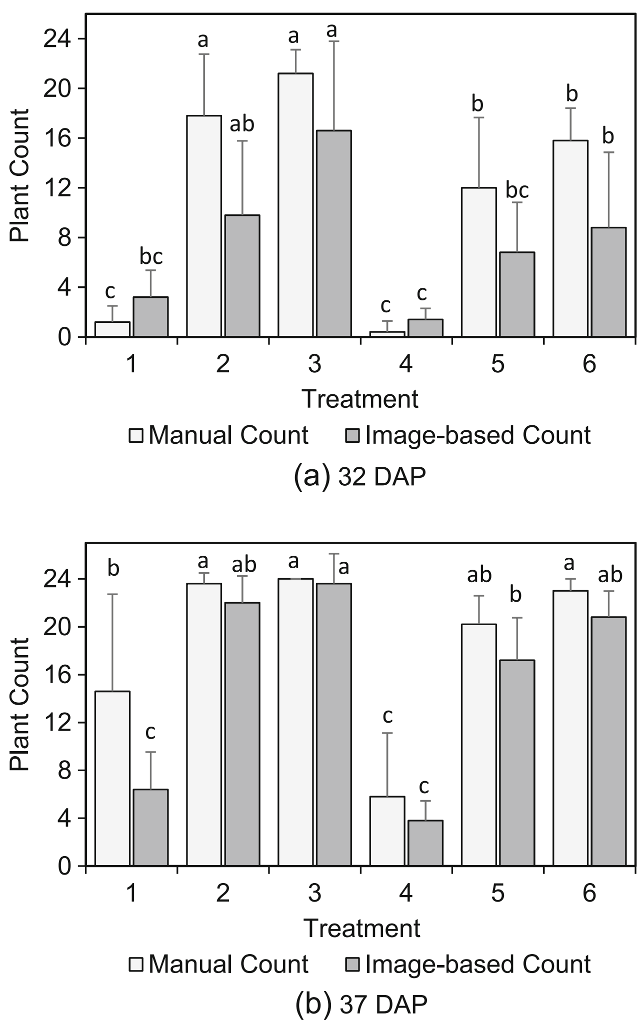


Fig. 3 Seed piece treatment effects on emergence, estimated as average number of plants emerged per treatment ($n = 5$), image-based count, and SUM-NDVI at **a** 32 DAP and **b** 37 DAP in 'Payette Russet'. Letters indicate HSD ($P < 0.05$) for comparison within a count type and sampling time

Previous literature has discussed the applications of remote sensing-based crop emergence evaluation in field crops (Yuping et al. 2008; Kipp et al. 2014; Sankaran et al. 2015) by looking at canopy cover, similar to the method reported in Patrignani and Oschsner (2015). However, the application of remote sensing in estimating the emergence of row crops such as potato has not been described. Given the complexity of potato production systems, remote sensing for phenotyping crop emergence can be of great value to agronomists and breeders. The results are encouraging for implementing the method for crop emergence evaluation under field conditions. Future studies should focus on imaging at a lower altitude with UAVs or from field based platforms, and implementation of reference markers or geo-referencing for automated plot segmentation.

Summary and Conclusion

This study presents a new application for high resolution multispectral imaging in estimating crop emergence in potatoes. Seed of two potato varieties that differed in length of dormancy and thus time to emergence was treated with plant growth regulators to create differences in plant emergence and establishment for evaluating the method. The multispectral images were captured at 32, 37, and 43 days after planting and features such as plant count, SUM-NDVI, and SUM-BINARY were extracted from the images. Image-based data were compared with manual plant counts. In general, there were significant correlations between image-based counts and SUM-NDVI with manual plant counts. The image-based features characterized the general treatment effects on potato emergence but underestimated the actual counts, partly due to conservative selection of the polygon threshold area used for resolving individual plants. However, the results demonstrated that high resolution aerial imaging is an effective high-throughput method for estimating crop emergence in potatoes and potentially other row crops.

Acknowledgements The authors thank Dr. Lav R. Khot, Center for Precision and Automated Agricultural Systems, Washington State University for his assistance in aerial data collection. This activity was funded, in part, with USDA National Institute for Food and Agriculture, Hatch Project, 1002864 (WNP00821).

References

Blauer, J.M., L.O. Knowles, and N.R. Knowles. 2013. Manipulating stem number, tuber set and size distribution in specialty potato cultivars. *American Journal of Potato Research* 90: 470–496.

Bouman, B.A.M., H.W.J. Van Kasteren, and D. Uenk. 1992. Standard relations to estimate ground cover and LAI of agricultural crops from reflectance measurements. *European Journal of Agronomy* 1 (4): 249–262.

Carlson, T.N., and D.A. Ripley. 1997. On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sensing of Environment* 62 (3): 241–252.

Eshel, D., and P. Teper-Bamnolker. 2012. Can loss of apical dominance in potato tuber serve as a marker of physiological age? *Plant Signaling and Behavior* 7 (9): 1158–1162.

Herman, D.J., L.O. Knowles, and N.R. Knowles. 2016. Differential sensitivity of genetically related potato cultivars to treatments designed to alter apical dominance, tuber set and size distribution. *American Journal of Potato Research* 93: 331–349.

Kipp, S., B. Mistele, P. Baresel, and U. Schmidhalter. 2014. High-throughput phenotyping early plant vigour of winter wheat. *European Journal of Agronomy* 52: 271–278.

Knowles, N.R., and L.O. Knowles. 2006. Manipulating stem number, tuber set, and yield relationships for northern-and southern-grown potato seed lots. *Crop Science* 46: 284–296.

Knowles, L.O., and N.R. Knowles. 2016. Optimizing tuber set and size distribution for potato seed (*Solanum tuberosum* L.) expressing varying degrees of apical dominance. *Journal of Plant Growth Regulation* 35 (2): 574–585.

Maris, B. 1988. Correlations within and between characters between and within generations as a measure for the early generation selection in potato breeding. *Euphytica* 37 (3): 205–224.

Midmore, D.J. 1984. Potato (Solanum spp.) in the hot tropics I. Soil temperature effects on emergence, plant development and yield. *Field Crops Research* 8: 255–271.

Novy, R.G., D.L. Corsini, S.L. Love, J.J. Pavek, A.R. Mosley, S.R. James, D.C. Hane, C.C. Shock, K.A. Rykbost, C.R. Brown, and R.E. Thornton. 2003. 'Alturas': A multi-purpose, russet potato cultivar with high yield and tuber specific gravity. *American Journal of Potato Research* 80: 295–301.

Novy, R.G., J.L. Whitworth, J.C. Stark, B. Schneider, N.R. Knowles, M.J. Pavek, L.O. Knowles, B.A. Charlton, V. Sathuvalli, S. Yilma, C.R. Brown, M. Thornton, T.L. Brandt, and N. Olsen. 2016. 'Payette Russet': a dual-purpose cultivar with cold-sweetening resistance, low acrylamide formation, and resistance to late blight and potato virus Y. *American Journal of Potato Research*. https://doi.org/10.1007/s12230-016-9546-0.

Patrignani, A., and T.E. Ochsner. 2015. Canopeo: A powerful new tool for measuring fractional green canopy cover. *Agronomy Journal* 107 (6): 2312–2320.

Rouse Jr, J., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. In Proceedings 3rd Earth Resources Technology Satellite (ERTS) symposium, Vol. 1 (pp. 309-317). Washington, DC, USA: NASA SP-351, NASA.

Sankaran, S., L.R. Khot, and A.H. Carter. 2015. Field-based crop phenotyping: Multispectral aerial imaging for evaluation of winter wheat emergence and spring stand. *Computers and Electronics in Agriculture* 118: 372–379.

Serrano, L., I. Filella, and J. Penuelas. 2000. Remote sensing of biomass and yield of winter wheat under different nitrogen supplies. *Crop Science* 40 (3): 723–731.

Sugiura, R., S. Tsuda, S. Tamiya, A. Itoh, K. Nishiwaki, N. Murakami, and S. Nuske. 2016. Field phenotyping system for the assessment of potato late blight resistance using RGB imagery from an unmanned aerial vehicle. *Biosystems Engineering* 148: 1–10.

Vina, A., A.A. Gitelson, D.C. Rundquist, G. Keydan, B. Leavitt, and J. Schepers. 2004. Monitoring maize (L.) phenology with remote sensing. *Agronomy Journal* 96 (4): 1139–1147.

Yuping, M., W. Shili, Z. Li, H. Yingyu, Z. Liwei, H. Yanbo, and W. Futang. 2008. Monitoring winter wheat growth in North China by combining a crop model and remote sensing data. *International Journal of Applied Earth Observation and Geoinformation* 10 (4): 426–437.

Zhou, J., M.J. Pavek, S.C. Shelton, Z.J. Holden, and S. Sankaran. 2016. Aerial multispectral imaging for crop hail damage assessment in potato. *Computers and Electronics in Agriculture* 127: 406–412.