

Erik Killian

04/22/2021

MontanaView Fellowship

Measuring Crop Emergence with Low Altitude Drone Imagery

Emergence is an early plant stage when the plant first breaks through the soil and begins photosynthesizing. Crop emergence is an important trait used by farmers and researchers alike. Measuring emergence is an early indicator for measuring germination rate and projecting yield estimates. Currently emergence is generally estimated through subsampling. Commonly hula hoops are thrown in randomized locations and plants are counted. The average plant density from these samples is extrapolated for the entire field. This approach ignores differences throughout the field and only measures a very small subsample. Utilization of unmanned aerial systems (UAS) could measure entire fields in a single flight, increasing sampling to include the entire population. With this project, I aim to create a high-throughput pipeline capable of processing high resolution UAS imagery to measure plant emergence across agricultural fields.

Current GIS and image processing software is extremely expensive. Using commercial programs like Pix4D and ArcGIS Pro can cost more than \$2000 per year, making them unapproachable for many farmers and researchers outside of the remote sensing field. For this project I solely use open-source software that is free for anyone to use.

Data was collected at Post farm in Bozeman, MT on a small wheat field using a Mavic 2 Pro UAS with integrated RGB camera. This setup with an iPad mini running free GS Pro flight planning software cost \$2000. NDVI is also commonly used in agricultural remote sensing. The Micasense Rededge sensor is popular for collecting near IR but is unnecessary for distinguishing plants from the surrounding soil. These sensors range \$5000 or more and require larger drone platforms to support long flight time.

Final resolution was about 0.2 cm as seen in figure 2, enough to distinguish plants from the soil. To achieve this resolution the UAS was flown at 25ft above the ground and paused flight for each image. This primarily helps reduce blurring of the images.

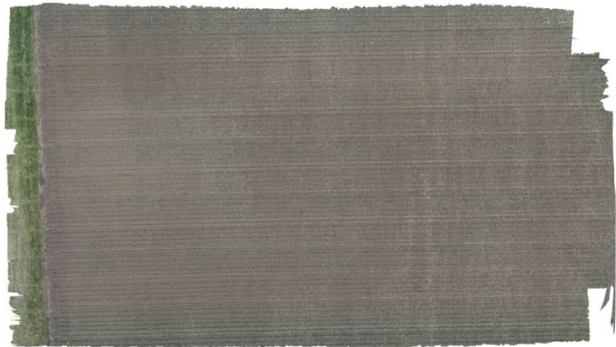


Figure 1: Stitched mosaic of 124 individual UAS images.



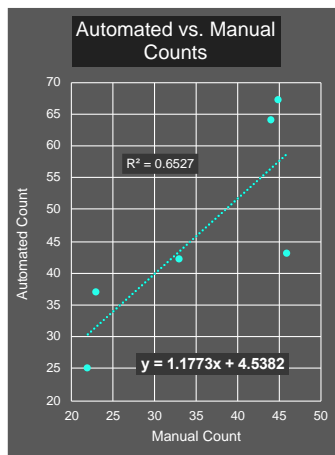
Figure 2: 0.2 cm resolution

Imagery was stitched using WebODM, the browser-based user interface for OpenDroneMap. This open-source software is designed to construct point clouds and resulting maps like 3D models and orthomosaic imagery. To allow for specific applications, there are many parameters available to change, but it represents a black-box approach. To improve processing time while maintaining native resolution, outputs were restricted to just the single orthomosaic image. DSM and DTM composites are also possible but proved time consuming.

Stitched imagery was exported to QGIS for image preparation. Here I needed to distinguish between plants and soil to enable automated counting of plants. To differentiate between pixels in an image I used the raster calculator to create a binary image mask – where 1 represents plant matter and 0 represents soil or other non-living plant material. There are many different indices popular in agriculture applications. Commonly the normalized difference vegetation index (NDVI) is used to measure plant vs surroundings. This index requires a sensor able to capture near infrared wavelengths, which are vastly more expensive and require larger payload drones. Conversely, there are many indices used that require only red, green, and blue light. I compared two popular solutions: Overall HUE and Excess Green. HUE compares red and blue to green, which I found measured soil color well, rather than highlighting plant material. The Excess Green index is simple, measuring $2 \times \text{Green} - \text{Red} - \text{Blue}$. Simply put it compares how green each pixel is relative to red and blue combined. I found this index extremely useful. With a threshold of 25 or more, I developed this test image of a plot (Figure 3).



Figure 3



Before attempting automated plant counts, I manually counted the color image to get a baseline. To automate counting I used FieldImageR, an R package suite designed around measuring mature corn test plots. To test on my imagery, I split my single plot image into 6 for each row (Figure 3). FieldImageR uses pixel group sizes to count plants on image masks. The threshold here will vastly change outputs. I finalized on 3-pixel threshold to account for noise in the mask. I directly compared my manual counts to the automated, with a final $R^2 = 0.65$. This correlation is not good enough to replace manual plant counting yet, but with changes to my approach and methods I believe I'll be able to achieve R^2 over 0.70.

For the 2021 field season, I am running another experiment including over 200 small barley plots at Post farm. I will continue flying for emergence on this field, improving from what I learned in this project. Most notable was my lack of ground truth data. This year I will take randomized counts across the field, including GPS points to relate to an orthomosaic. This will create a much stronger baseline to compare automated counts with. Finally, I would also like to automate my workflow. Currently each step is performed manually, but with batch processing I would be able to analyze much more data.