REMOTE SENSING with small unmanned aircraft systems (UAS) is advantageous for agriculture (Zhang and Kovacs, 2012; Maes and Steppe, 2019) and may be classified into three general categories: scouting for problems, monitoring crop growth, and planning management operations (Hunt and Daughtry, 2018). Typically, UAS images are acquired with large front-to-back and side-to-side overlap to create ortho-rectified mosaics. A fixed-wing UAS was flown over six center-pivot irrigated fields and untilled sagebrush steppe over the 2014 growing season. A 90-m by 90-m area centered at the image nadir point was analyzed as a single point along a linear transect. When aggregated by field, UAS normalized difference vegetation index (NDVI) agreed with NDVI from a corresponding Landsat image, with an $R^2$ of 0.958 and an RMSE of 0.058. Since each image retained its high spatial resolution, the proposed transect method could be used along with computer vision and artificial intelligence to detect plant stress, weeds, pests, and diseases.

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Core Ideas

- Monitoring crops over time requires methods that are very low cost.
- Currently, unmanned aircraft system images have large overlap to create ortho-rectified mosaics.
- Instead, each image may be used as a sample point along a flight transect.

Research Letters

Linear Transects of Imagery Increase Crop Monitoring Efficiency Using Fixed-Wing Unmanned Aircraft Systems

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Abstract: Crop monitoring with unmanned aircraft must be timely to prevent yield losses and have low cost to be profitable. However, the expenses of acquiring large numbers of images with large overlap and creation of ortho-rectified mosaics may make unmanned aircraft system (UAS) monitoring slow and cost prohibitive. A fixed-wing UAS was flown over six center-pivot irrigated fields and untilled sagebrush steppe over the 2014 growing season. A 90-m by 90-m area centered at the image nadir point was analyzed as a single point along a linear transect. When aggregated by field, UAS normalized difference vegetation index (NDVI) agreed with NDVI from a corresponding Landsat image, with an $R^2$ of 0.958 and an RMSE of 0.058. Since each image retained its high spatial resolution, the proposed transect method could be used along with computer vision and artificial intelligence to detect plant stress, weeds, pests, and diseases.

Methods

Six 50-ha, center-pivot irrigated fields were selected in north-central Oregon, USA, at about 45.68° latitude, −119.89° longitude, and 215 m elevation above mean sea level. (Fig. 1A).

Abbreviations: L8-OLI, Landsat 8 Operational Land Imager; Mini-MCA, miniature multiple camera array; NDVI, normalized difference vegetation index; UAS, unmanned aircraft system.
According to the 2014 Cropland Data Layer (USDA National Agricultural Statistics Service, 2014), the crops planted were three fields of potato (*Solanum tuberosum* L.), one field of maize (*Zea mays* L.), and two fields of spring wheat (*Triticum aestivum* L.). To extend the range of apparent surface reflectance, two areas of untilled sagebrush steppe directly south of the fields (e) and (f) were used (Fig. 1A). The dominant species were sagebrush (*Artemisia tridentata* Nutt.) and cheatgrass (*Bromus tectorum* L.).

To cover large areas in short amounts of time, low-altitude long-endurance fixed-wing aircraft are required. Four UAS flights were conducted (Table 1), each following a looped pattern with straight flight lines over the six fields (Fig. 1A). The air space is defined as a Military Operations Area, which allows UAS flights well above 120 m above ground level.

The multispectral sensor used on the fixed-wing aircraft was a Tetracam, Inc., Miniature Multiple Camera Array (Mini-MCA) with six cameras. Five cameras had wavelength filters (± 10 nm full width half maximum): blue (470 nm), green (550 nm), red (660 nm), red-edge (710 nm), and near-infrared (810 nm). Image size for each camera was 1024 rows by 1240 columns, with the rows aligned with the flight direction. The sensor’s pitch (pixel) size was 5.2 mm, and the lens focal length was 8.5 mm. From an altitude of 450 m, the ground sample distance was 24 cm and the field of view was 5 ha. Data were acquired in a 10-bit raw format and converted to 16-bit TIFF files using Tetracam’s PixelWrench 2 software.

The sixth camera of the Mini-MCA was used for Tetracam’s Incident Light Sensor (Heinold, 2014), which converts digital numbers to surface reflectance using the PixelWrench 2 software. A script written in ENVI version 5.5.2 (Harris Geospatial Solutions) created a 90-m by 90-m region of interest around the image nadir point. The reflectance means were used to represent the image as one point along the transect. Aircraft pitch averaged 5°; thus, the nadir point was about 200 pixels from the image center point. Images were excluded when the aircraft had excessive pitch (>7.5°) or excessive roll (less than −3.0° or greater than 3.0°). The angle between the sun and the surface of the Incident Light Sensor varied with aircraft bearing, flight date, and time of day (Table 1). The variation was reduced using a normalized difference vegetation index (NDVI):

$$\text{NDVI} = \frac{(R_{\text{NIR}} - R_{\text{Red}})}{(R_{\text{NIR}} + R_{\text{Red}})}$$  \[1\]

where $R_{\text{NIR}}$ and $R_{\text{Red}}$ are the surface reflectances of the near-infrared and red bands, respectively (Rouse et al., 1974).

There were no ground data for comparison with the Mini-MCA reflectances. Landsat data were used for comparison because (i) the data are independent of the Mini-MCA reflectances, (ii) an image covers the whole area,
and (iii) the reflectances are calculated using MODTRAN 6 (MODerate resolution atmospheric TRANsmission) model (Berk et al., 2014). Landsat 8 Operational Land Imager (L8-OLI) imagery (path 044, row 028) collected nearest to the day of each flight (Table 1) were atmospherically corrected to surface reflectance with the ENVI module, Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH).

The latitude and longitude recorded for each Mini-MCA image was used as the center point for a 3-pixel by 3-pixel region of interest in the corresponding Landsat image for calculating mean NDVI from Eq. [1]. For each date, point NDVI from Landsat and Mini-MCA were aggregated by field to calculate overall mean NDVI. The agreement between Landsat and Mini-MCA NDVI was assessed using linear regression.

Results and Discussion

During June and July 2014, the spring wheat fields ripened and were harvested, leading to decreased L8-OLI NDVI over time (Fig. 1B), whereas the maize field grew to maximum leaf area as shown by increased NDVI over time. The three fields of potato and the sagebrush steppe showed little change in L8-OLI NDVI (Fig. 1B).

Mini-MCA images were acquired every 2 s. The average distance between two images when the UAS flew southeast with the wind ranged from 76 to 81 m, whereas the average distance when flying north-west against the wind was 58 to 70 m. On 4 June, there were five flight lines over each field spaced 160 m apart (Fig. 2B). The Mini-MCA imagery had no side-to-side overlap, so on 19 June, seven flight lines over each field spaced 114 m apart were acquired (Fig. 2D). On 8 July and 21 July, eight flight lines spaced 100 m apart were obtained for each field (Fig. 2F and 2H).

A comparison of Mini-MCA NDVI (averaged for an area of 90-m by 90-m) and L8-OLI NDVI (averaged for 3 by 3 pixels) showed large amounts of scatter but were significantly correlated. This occurred in part because of the large number of observations and in part because of the addition of rangeland to the south extended the range of NDVI. The scatter was still large when the data were stratified by date, but there were no systematic differences among dates that would indicate changes in Mini-MCA camera calibrations. Most of the scatter was found around the field borders (Fig. 2), where small errors in location may have caused large changes in mean NDVI.

Averaging the data by field resulted in a high correlation between Mini-MCA and L8-OLI data (Fig. 3). The coverage from the flight-line transects accurately represented the spatial and temporal distribution of NDVI seen in the Landsat images. The cluster of points at about NDVI = 0.2 and NDVI = 0.9 were expected to make the correlation significant, so the data for the fields with intermediate NDVI were examined. These fields had a large range in NDVI, which is similar to NDVI variation around the field borders; thus, small errors in location may have created large variation.

An important point about use of flight-line transects for monitoring is that an image is not the final data product (Hunt and Daughtry, 2018). Individual images are reduced to a point at a specific latitude and longitude, which is put into context by a geographic information system. However, compared with an ortho-rectified mosaic, geographic locations are expected to be less accurate because the image it is not constrained from being stitched with the surrounding...
images. The location errors are not simply due to the accuracy of the global navigation satellite systems (GNSS). The accuracy of UAS attitude from an inertial motion unit is coupled to both the measured altitude and the measurement accuracy. Most UAS used in research are multicopter aircraft, which are stable platforms for remote sensing but have flight times of limited duration. Will the lower accuracy of fixed-wing aircraft be detrimental to adoption for monitoring agricultural fields? It will depend on the data products used by the farmers.

Monitoring is not restricted just to analyzing changes in NDVI. At low altitudes, individual plants may be counted for calculation of germination rates, plant density, and plant survival (Gnädinger and Schmidhalter, 2017; Zhang et al., 2018; Buters et al., 2019). Plant cover may be calculated from the number of pixels with high NDVI (Hunt and Daughtry, 2018). Thermal infrared sensors may be used for detecting drought-stressed or disease-infected plants (Franceschini et al., 2019; Maes and Steppe, 2019). Furthermore, very high resolution imagery from UAS may be analyzed by a combination of computer vision and artificial intelligence to detect weed species and pest infestations. However, to be successful in preventing yield losses requires monitoring several times over a growing season.

**Conclusions**

Monitoring is meant to provide timely information that allows a farmer to avoid yield losses. Typically, UAS images are acquired with large front-to-back and side-to-side overlap to be stitched into an ortho-rectified mosaic. We proposed that UAS images may be analyzed like plots along field transects to sample crop status. Without overlap, monitoring is more efficient and thus should have lower cost. We showed that the coverage from flight-line transects accurately represented the spatial and temporal distribution of NDVI in a sequence of Landsat images over irrigated cropland. While the final products may have lower geolocation accuracy, the undiluted high-spatial resolution of each image may allow information other than NDVI to be obtained.

**Conflict of Interest**

The authors declare no conflict of interest.

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**References**


