High-Resolution Mapping of Tile Drainage in Agricultural Fields Using Unmanned Aerial System (UAS)-Based Radiometric Thermal and Optical Sensors

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Abstract: With the growing concerns of water quality related to tile drainage in agricultural lands, developing an efficient and cost-effective method of mapping tile drainage is essential. This research aimed to establish mapping of tile drainage systems in agricultural fields using optical and radiometric thermal sensors mounted on Unmanned Aerial System (UAS). The overarching hypothesis is that in a tile-drained land, spatial distribution of soil water content is affected by tile lines, therefore, contrasting soil temperature signals exist between areas along the tile lines and between the tile lines. Designated flights were conducted to assess the effectiveness of the UAS under various conditions such as rainfall, crop cover, crop maturity and time of the day. Image correction, mosaicking, image enhancements and map production were conducted using Agisoft and ENVI image analysis software. The results showed intermediate growth stage of soybean plants and rainfall helped delineating tile lines. In-situ soil temperature measurements revealed appropriate time of the day (14:00 to 18:00 h) for thermal image detection of the tile lines. The role of soil moisture and plant cover is not resolved, thus, further refinement of the approach considering these factors is necessary to develop efficient mapping techniques of tile drainage using UAS thermal and optical sensors.

Keywords: tile drainage; thermal sensor; optical sensor; image processing; UAS; remote sensing

1. Introduction

Modification of a watershed to improve productivity of agricultural lands is a common practice around the globe. Installation of tile drainage systems, modification of surface drainage and retention ponds are among the few types of watershed modification techniques [1]. Agricultural subsurface drainage also known as tile drainage [2,3] (hereinafter referred to as ‘tile drainage’) is the most widely used conservation method since the earliest civilizations of Mesopotamia and Iran before 4000 BC [4,5]. Tile drainage removes water from the soil, with poor drainage characteristics and found in a relatively flat to gentle-sloped watersheds, preventing flooding that hinders the functionality of the land [6,7]. As a result, people can utilize much of the land for recreation and agricultural purposes. In the Mid-western region of the United States, extensive agricultural land was obtained through installation of tile drainage [8,9]. However, mostly there are no records indicating the location of tile drainage in much of the Mid-west, due to various reasons such as a change in ownership and lack of proper documentation.

Tile drainage provides a tremendous advantage for agronomy by improving soil moisture conditions and inducing aeration, reducing total surface runoff (flooding) and erosion and increasing infiltration [10–13] and trafficability. The removal of excess water improves aeration and microbial activity, thereby creating suitable soil conditions to attain good crop productions [14]. Dry soil warms up faster than wet soil, tile drained soil surface dry faster and allows earlier land preparation and early spring planting for the farmers [14]. Though tile drainage has positive agronomic advantages, it presents a negative impact on
the environment. Tiles relatively quickly drains the water from the agricultural land into receiving water systems such as streams. As a result, tile drainage allows a direct flow path of nutrients from agricultural lands to streams, a potential water quality concern [12]. Generally, tiles can deliver substantial amounts of dissolved nutrients (e.g., nitrate) into surface water bodies [15]. In addition, tile drainage systems lower soil moisture in the soil and maintain a lower water table and potentially increase the volume of water draining from the field and reduce the water retention time in the soil zone. The faster the water drains and reduction in retention time results in faster washing of nutrients to the stream. Thus, high nutrient loss from agricultural lands degrade soil fertility and impair water quality of receiving waters. This has a huge impact on the environment creating algal blooms and hypoxic zones in receiving water bodies. For example, water quality problems associated with nutrient loss was observed in the Great Lakes, Gulf of Mexico, Baltic Sea and Lake Winnipeg, among others [16].

Locating tile drainage is perhaps important to the farmers because productivity is highly dependent on efficiency of the tile drainage. It is also essential to better understand environmental impacts associated with tile drainage. For example, estimates of the contribution of tile flow and load from farm fields and water quality and hydrological modeling of watersheds containing tile drainage requires knowledge of the location of tile lines and measurement of density and spacing between tile lines. Therefore, proper, cost-effective and efficient mapping techniques are necessary to locate tile lines. Furthermore, such techniques help identify and locate malfunctioning of tile drainage due to aging and prolonged utilization where the tiles are filled with sediment, mosses or dirt to the point that hinders infiltration and movement of water through them. Locating such tiles helps the farmers replace the old (malfunctioning) tiles which increases the overall productivity of the farmland.

Various techniques, using geophysical instruments and remote sensing, have been developed to map tile lines. The Ground Penetrating Radar (GPR) is the most reliable method with high accuracy of delineating tile drainage [17–20]. However, GPR is costly, labor intensive and time consuming to map tile drainage over large fields. Remote sensing-based techniques through processing of aerial photography and using optical remote sensing satellites proved potential of mapping tile drainage [21]. The aerial photography techniques integrate additional information such as landcover, soil drainage class and surface slope to map tile drainage [16,21]. This technique is limited to determining the total percentage of land area that is tile drained and fails to detect individual tile locations. Satellite-based remote sensing data have been used for various hydrological and resources applications including mapping tile drainage [22]. The optical satellite technique compares reflectance values of imageries taken before and after rainfall based on the assumption that tile drainage drain water faster and have higher reflectance values compared to non-tile drained area. Limitations of satellite remote sensing method include lower spatial resolution and effect of cloud cover on getting good quality imagery taken before and after a rainfall [23–25].

Development of Unmanned Aerial Systems (UASs) piqued interest to the scientific community in wide areas of applications including precision agriculture [26], hydrology [27] and environmental sciences [28]. Improvement of sensor technology and processing capability provides opportunities for accurate measurement and mapping of land surface features. Compared to satellite remote sensing, UASs have advantages in terms of flexibility, high temporal and spatial resolution and cost. Unlike satellite remote sensing, the UAS is the best alternative for mapping with little or no effect of cloud cover.

In this study, UAS-based tile lines mapping technique was employed to map tile lines in agricultural fields in central Illinois. Very limited studies conducted to map tile lines using sensors mounted on UAS. For example, Allred et al. [18] used thermal sensor on a corn field and found that thermal sensors are capable of mapping tile drainage effectively as compared to the visible-infrared and near-infrared sensors. The limitation of this research is that no thermal sensor was flown under different soil, rain and temperature conditions.
Woo et al. [29] explored a small-scale experimental device simulating agricultural land and tile drainage and used temperature sensors to map the tile lines and the result indicated a promising tool to locate tile drainage. The objective of this research is to map tile drainage using thermal and optical sensors mounted on UAS and assess the effect of different field conditions including the effect of time of the day (temperature variation), rainfall, crop cover and growth stage (height) of crops on the land were evaluated to establish appropriate mapping conditions.

The overarching hypothesis of this research is based on the fact that tile drainage may produce distinct spatial distribution of soil moisture on the land surface. Dry soils warm up faster than wet soils form the basis of this research. The ability of a dry soil to store and release heat is different from the capacity of a moist soil to store and releases heat [30]. After a rainfall, soils above the tile lines get quickly dry relative to areas between the tile lines (Figure 1). This is because the tiles drain water from the soil at a faster rate above the tile lines compared to adjacent non-tiled region (between tile lines). Soil moisture being one of the factors affecting soil temperature, the temperature of the soil above the tile lines expected to be different from areas in-between tile lines. The lowering of soil moisture above the tile lines decreases soil heat capacity thereby increasing in surface soil temperature [29]. As a result, there would be a variation of thermal inertia, the degree of slowness with which the temperature of a material approaches that of its surroundings, during diurnal fluctuation of temperature in the soil. This assumption led to the testing of the applicability of thermal sensor to map tile lines in this research. In addition, optical sensor, which was used to produce visual images and to create Digital Surface Models (DSM), augmented the thermal method. This is because tile lines produces surface depressions due to compaction where soil particles make adjustment, in the modified soils due to ditching and installation of the tile lines. Further, tile drainage improves soil conditions and results in crop performance variability in the field which can be detected by optical and/or thermal sensors.

![Figure 1. Conceptual diagram (cross-section) showing tile drainage and assumed subsurface moisture variation along and between tile lines (blue shading indicates water saturation).](image)

2. Study Site

The study site is located 18 km north of Normal town in central Illinois, USA. The location of the tile lines in the study site is known and existing tile lines map (Figure 2) is available, which can be used to compare and validate against the results from this study. Two types of tiles installed in the area; 10 cm diameter tiles that serve as tributaries and 20 cm diameter main tile that empty into an experimental wetland and then to the nearby creek (Figure 2). The site is an agricultural field with alternating soybean and corn grown in the area. The site has an area of 0.24 km$^2$ (24 ha) and has nearly flat topography with rolling hills and slopes ranging from 0 to 5%. Silty clay loam and silty clay characterize the soils in the area which is derived from glacial deposits. The site is located on the Bloomington ridge plain physiographic region of Illinois, characterized by gently sloping, broad ridges
formed by moraines and flat lacustrine Plaines. Specifically, the study site is located on Normal and Bloomington moraines that are part of Batestown till member [31]. It also contains the Cahoka formation which includes deposits of glacial outwash along the larger valleys, alluvial sand, silt, clays and thin deposits of loess (windblown silt).

**Figure 2.** Location map of the study site, existing tile lines map (red lines), location of soil temperature probes (yellow circles) and background is orthomosaic image collected using Unmanned Aerial System (UAS).

### 3. Methods and Data

#### 3.1. In-Situ Soil Temperature

The appropriate time for the acquisition of thermal images was explored, first, using in-situ soil temperature measurements. The objective is to find a proper time of the day that maximizes the thermal contrast between areas close to tile lines and in-between tile lines. Two sets of decagons Em59G remote loggers with soil temperature and moisture probes were installed right on top of the tile lines and in-between tile lines. Each logger has 5 probes installed at 1 m spacing parallel to the axis of the tile line. The average depth of the measurement is 5 cm. Tile spacing between adjacent tile lines is approximately 20 m. The spacing between the two sets of probes was 10 m, one set installed right above the tile line while the other mid-way (at 10 m) between two adjacent tiles lines (Figure 2). The device was set to take a measurement every 5 min and collected data for 15 days. Temperature data were analyzed to get the time where there is a significant difference in temperature between the measurements taken on the tile line and areas in between tile lines.

#### 3.2. Sensors

**Thermal and Optical Sensors**

The thermal sensor was used to identify the distinct surficial soil temperature variability caused by tile lines. Whereas the optical sensor was helped visual interpretation and used to build Digital Surface Model (DSM) [32,33], which is the equivalent of a Digital Elevation Model (DEM) that gives a very high-resolution (centimeter-scale) 3D representation of the surface drainage pattern and water flow. During the preliminary data collection from different farmlands outside the study site, surface depressions indicating tile drainage location were observed using a 10 m resolution DEM. Optical sensors help obtain centimeter-scale resolution and alleviate the resolution constraint to improve the visibility of surface features. The Forward Looking InfraRed (FLIR) Vue Pro R thermal camera and the DJI optical camera were used. See Table 1 for detail specifications.
Table 1. Thermal and optical camera specifications used for the data collection.

| Parameter                  | FLIR Vue Pro R | DJI FC 6510 ZENMUSE X4S SPECS | DJI FC330 Phantom 4 Quadcopter |
|----------------------------|----------------|-------------------------------|-------------------------------|
| Spectral Range             | 7.5–13.5 µm    | 380–740 nm                    | 380–740 nm                    |
| Frame Rate                 | 30 Hz          | 14 frames per second          | 30 frames per second          |
| Data Format                | Radiometric jpeg | DNG, JPEG, DNG+JPEG       | JPEG, DNG RAW                 |
| Sensor Resolution          | 640 × 512      | 16:9 (5472 × 3078), 4:3 (4864 × 3648) | 12 MP (4000 × 3000) |
| FOV                        | 45° × 35°      | 84°                           | 94°                           |
| Thermal Sensitivity (NETD) | 0.02 °C        | N/A                           | N/A                           |
| Focal length (mm)          | 13             | 24                            | 20                            |
| Weight (g)                 | 92–113         | 253                           | 190                           |

3.3. UAS Flight Planning

All flight information, such as flight date and time, flight altitude, type of sensors used and weather conditions is summarized in Table 2. A total of seven flight missions are accomplished. Ten Ground Control Points (GCPs) were collected using Tremble Geo7x GPS to make a geometric correction during image processing. The flights were designed to counter field conditions such as rainfall, crop cover and time of day with maximum thermal inertia between the tile lines and the adjacent zones.

Table 2. Detailed flight information during data collection, study site was covered with soybean crop for all flights except for the flight conducted after harvesting on 24 October 2019.

| Type of Camera | Flight Date | Flight Started | Flight Ended | Weather Condition (Max T. °C/Min T. °C) | Flight Altitude ABGL (m) | No. of Images Collected |
|----------------|-------------|----------------|--------------|------------------------------------------|--------------------------|-------------------------|
| FLIR Vue Pro R 640 | 22 July 2019 | 17:20:22       | 18:03:30     | 27/15 °C, partly cloudy, 24.4 mm rain on 5/7/2019 | 45                       | 733                     |
|                 | 29 July 2019 | 16:51:40       | 17:27:14     | 31/18 °C, cloudy, 2.3 mm of rain on 27/7/2019 | 45                       | 645                     |
|                 | 30 July 2019 | 16:04:02       | 16:43:28     | 29/20 °C cloudy, 16.8 mm of rainfall the night before | 45                       | 750                     |
|                 | 24 October 2019 | 17:05:24     | 17:50:34     | 13/5 °C, Cloudy, 3.6 mm rain on 21/10 | 45                       | 628                     |
| DJI FC 6510 ZENMUSE X4S | 6 August 2019 | 17:04:14       | 17:30:14     | 18/19 °C, Partly cloudy, 6.9 mm rainfall in the morning | 100                      | 348                     |
|                 | 24 October 2019 | 15:15:00       | 15:30:00     | 13/5, Cloudy, 3.6 mm rain on 21/10 | 100                      | 356                     |
| DJI FC330 phantom 4 Quadcopter | 15 July 2019 | 15:49:02       | 16:02:02     | 30/19 °C, windy and cloudy | 60                       | 325                     |

3.4. Data Processing and Analysis

3.4.1. Visible Image

Agisoft Metashape software (v 1.5.4) [34] is used to process the visible images taken by phantom 4 and Zenmuse X4S cameras. The Agisoft software uses photogrammetry and computer vision algorithms to generate high resolution georeferenced orthomosaics, digital surface model and textured polygonal models by transforming 2D maps to 3D maps and models [35]. The parameter setting called quality and depth filtering is set to Ultra-high and aggressive, respectively.

3.4.2. Thermal Image

The lack of geographic information (due to the lack of communication between the sensor and drone) of the thermal images makes the processing complex. First, Geoset-
ter software (version 3.5.3) [36] was used to register each image’s geocoordinates by matching the time stamp of each image with flight log data. The timestamp of the image is used to synchronize the image timestamp with the timestamp of the GPS tracklog found in the flight log data. After getting the image coordinates, Pix4D software was used to create mosaic thermal images.

3.4.3. Data Analysis

ENVI image analysis software (analysis were done using ENVI 5.5.1) [37] was employed to perform image processing. First, image stretching, a linear percent stretch function, has been used. A linear percent stretching enables trimming extreme values from both ends of the histogram of the pixel values using a specified percentage. Accordingly, the 5% linear stretching function was employed as it showed the best contrast. After stretching the images, convolution and morphology filters were used. Convolution filters operate based on the brightness value of a given pixel. A $5 \times 5$ kernel size was selected for the filter mask. The directional filter provided the best result for delineating the tile lines. The analysis was conducted by dividing the study site into four fields based on the direction of the tile lines as noticed from the temperature anomaly and pre-existing tile drainage map (Figure 2).

After directional filtering, supervised classification is conducted by training the data using two training classes based on the range of temperature values of each pixel. The classification method was set to a minimum distance. A minimum distance uses mean vectors for each class and calculates the Euclidean distance from each unknown pixel to the mean vector for each class. Then the pixels are classified to the nearest class. Minimum distance classification calculates the Euclidean distance for each pixel in the image to each class:

$$D_i(x) = \sqrt{(x - m_i)^T(x - m_i)}, \quad (1)$$

where:

- $D_i$ = Euclidean distance
- $i$ = the $i$th class
- $x$ = $n$-dimensional data (where $n$ is the number of bands)
- $m_i$ = mean vector of the class $i$

The results from supervised classification were further enhanced to refine the classification result by using two methods, including enabling smoothing and enabling aggregation. Enabling smoothing helps to remove speckling noises created during classification. A $5 \times 5$ smooth kernel size was used for smoothing, whereas the aggregate minimum size is set to the default value of 9. Regions with a size of 9 or smaller are aggregated to an adjacent, larger region. The entire methodology followed in this study is outlined in Figure 3. Calibration of thermal imaging camera using in-situ temperature data was not implemented as the FLIR Vue Pro R camera used in this study gather reliable, non-contact temperature measurements from an aerial perspective.
4. Results

4.1. In-Situ Soil Temperature

Figure 4 shows the fluctuation of in-situ soil temperature differences collected from near tile line and in-between tile lines. The probes installed along the tile line showed a relatively higher temperature during the nighttime and lower temperatures during the daytime than the probes installed between tile lines caused by thermal inertia. Comparing the two temperature measurements (on the tile line and area between the tile lines), maximum temperature contrasts are generally observed in the afternoon between 11:00 and 18:00 h with peak differences around 15:00 h (Figure 4). In the afternoon, the soil temperature along the tile line becomes higher than the temperature between the tile lines. Thus, all the UAS thermal data collection is conducted in the afternoon hours between 14:00 and 18:00.

Figure 4. Plot of in-situ soil temperature difference between soil temperature measured in between the tile line and on the tile line, with time of the day in the x-axis. The highest temperature difference between the tile and non-tiled area occurred between 11:00 AM and 6:00 PM local time and peaked (ΔT~3 °C) at around 3:00 PM local time.
4.2. UAS Optical Imagery

Figure 5a,c,e are orthomosaic maps created from imageries collected using optical sensor at different times and conditions. Figure 5a,c were collected under crop cover (soybean) conditions, while Figure 5e collected after harvesting (no crop cover). The map in Figure 5a was taken at early growth stage of the soybean. As seen in both maps Figure 5a,c the vegetation density is different. In Figure 5a, we can see more distinctive patterns of growth of the soybean plants. Whereas Figure 5c represents more matured soybeans and has a dense population of soybeans, it shows uniform growth on the left part of the study site while distinct patterns are visible on the right side of the study site. The map from 24 October 2019 (Figure 5e) with no crop cover exhibits no patterns unlike the other orthomosaic maps.

Figure 5. Orthomosaic maps and Digital Surface Models (DSMs) from UAS data collected at different times (a,c) on 15 July 2019, (b,d) on 6 August 2019, (c,e) on 24 October 2019. The maps on the left side are DSMs while on the right side are the corresponding orthomosaic maps.

4.3. Digital Surface Model (DSM)

Figure 5b,d,f display the DSMs of the study site. The effect of the crop cover (soybeans) is recognized with distinct patterns on the DSMs (Figure 5b,d) as compared to the no cover crop DSM (Figure 5f). The pattern of the taller soybean plants aligns well with the orientation of the tile lines. For example, the image captured on 6 August (Figure 5b) shows more distinct signatures of the tile line than the image captured on 15 July 2019 (Figure 5a) at the early growth stage of the soybeans. The height of the crop cover played a significant role. The DSM was expected to show the depressions parallel to tile lines.
caused by the compaction of the soil refill after the construction of the tiles. However, no significant feature indicating the tile lines were observed, especially from the DSM with no crop cover except the showing the overall topography of the study site.

4.4. Radiometric Thermal Imagery

The radiometric thermal imageries collected on 22 July, 29 July, 30 July and 24 July 2019, among which the last three imageries are collected following a rainfall, were processed and analyzed. The thermal Maps based on flights collected after rainfall were able to show the tile lines well.

Figure 6b,c compared to the thermal imageries collected during dry conditions (Figure 6a). Figure 6d was taken on 6 August 2019, with rainfall in the morning. The mosaicking for this data was incomplete due to homogenous nature of the individual thermal images, specifically in the southern part of the study site. Though Figure 6d collected after rain event, maturity of the soybean plant, which we believe created homogenous thermal signal, interfered with defining the tile lines. The dark-colored patch of a line (indicated by white arrows, see the figures below) that runs from south to north on the lower right section and upper left section of the study site (Figure 6c) aligns well with the pattern of the line observed on visible images and DSM (Figure 5). Further, these signatures align well with the existing surveyed map of the tile lines. The thermal map in Figure 6a (flight on 22 July 2019), collected under dry condition, shows the signature of the tile lines mainly due to the crop cover, preferentially the soybean plants grown following the tile lines. On the other hand, the thermal imagery from 24 October 2019 has no soybean cover and displayed no tile signature. The summary statistics showed the ground temperature ranging from 15 to 64 °C, with a mean temperature of about 33 °C and the interquartile range extending from 5 to 10 °C (Table 3). Most of the soil temperature values were between 25 and 45 °C with some outliers that mainly come from objects on the ground, such as metals, asphalt roads and equipment.

![Figure 6](image-url)  
**Figure 6.** Thermal maps derived from radiometric thermal images collected at different days: (a) dry condition, on 22 July 2019, (b) After rainfall, on 29 July 2019, (c) After rainfall, on 30 July 2019 and (d) rain in the morning, on 6 August 2019. The actual ground temperature varies between 30 °C to 45 °C. The white arrows are showing the dark lower-temperature line running parallel to the tile lines.
Table 3. Summary statistics of temperature values from the radiometric thermal imageries collected at different days.

| Statistical Parameter          | 22/7/2019 | 29/7/2019 | 30/7/2019 |
|-------------------------------|-----------|-----------|-----------|
| Min. Temperature              | 15.01     | 20.82     | 15.03     |
| 1st Quartile                  | 29.17     | 32.41     | 32.69     |
| Median                        | 31.18     | 33.9      | 34.59     |
| Mean                          | 31.43     | 34.66     | 36.06     |
| 3rd Quartile                  | 33.41     | 36.18     | 38.27     |
| Max Temperature               | 49.95     | 59.02     | 63.94     |
| IQR (interquartile Range)     | 4.83      | 7.27      | 9.46      |

4.5. Image Processing

Figure 7 produced through image processing including correction for sharpness, contrast and brightness, image filtering, supervised classification and image smoothing and aggregation. For interpretation purposes, the area was divided into four zones, Zone I, Zone II, Zone III and Zone IV. The image processing results have greatly enhanced the visibility of tile drainage, especially in Zone II. Zone I and Zone III have shown less visibility to the tile lines. Further processing of the thermal imagery (e.g., after directional filtering), the pixel values across the tile lines showed distinct signals right at the tile locations.

5. Discussion

In-situ soil temperature data depicted that significant contrast in ground temperature was observed between temperature measurements conducted near tiles and in-between tile lines. This was caused by thermal inertia [38], the degree of slowness with which the temperature of a body approaches that of its surroundings, caused by the variation in soil moisture conditions between these locations due to the presence (or absence) of tile drainage. Further, this variation is governed by the time of the day, where the temperature difference between near tiles and between tile lines becomes the highest (Figure 4). The largest difference in temperature occurred in the afternoon. This helped identify
the optimal time where there is significant thermal contrast between the near tile and non-tiled locations.

The optical imagery played a role in identifying the locations of the tile lines. For example, the image collected on 6 August 2019, displayed the soybean plants developed following linear patterns parallel to the tile lines. This could be due to optimal growth conditions (e.g., aeration, moisture flow and temperature) created by the tile drainage that favor the relatively healthier development of the plants (Figure 5a,c). As the plant density increases, those linear patterns become less conspicuous from the optical imageries (Figure 5c). Figure 5c collected at a later stage of growth compared to Figure 5a. Further, some of those linear patterns are depicted by high resolution DSMs (Figure 5b,d). Again, the ability of the DSMs showing the patterns is highly dependent on the crop cover.

Similar to the optical imageries and DSMs, the thermal imagery was able to depict the drainage patterns. On the thermal imageries (Figure 6), the tile lines are characterized by relatively low temperature zones (darker tones) while areas with sparse soybean plants (or bare soil) are characterized by higher temperature (brighter tones). Note that there are clear patterns of the lines depicted by the thermal images (Figure 6b,c). The temperature anomaly near the tile lines is unexpected, somewhat contrary to our hypothesis, where dryer soils near the tile lines warm up faster. This is due to the soybean plant cover. The plant cover can change soil thermal properties [39] by shading the soil and helps reduce soil moisture evaporation. Considering the brighter regions (higher temperature), these are bare or sparsely plant covered areas soil evaporation is heightened. The thermal imagery was collected on 24 October 2019. (No plant cover) showed no distinct patterns of ground temperature. From this and reasons discussed above, we concluded that soybean plants cover played significant role in showing the drainage patterns. However, this neither proves nor disproves the need for plant cover on the land surface for this approach to apply.

We believe the season was a factor in the bare soil map. The 24 October 2019 data was collected in the fall season. The weather condition is relatively colder and the air temperature is almost similar to subsurface water temperature and showed a homogenous thermal response (Figure 8). The no plant cover (bare soil) hypothesis has to be tested in other seasons, for example, in late spring before planting season when the temperature is high. Figure 8 shows thermal images from the same location that are used to compare the thermal signals before and after harvesting. The comparison indicates that crop covered images taken on 30 July 2019 (Figure 8a,b) showed the tile lines compared to images collected on 24 October 2019 after harvesting (Figure 8c). The homogeneity of the temperature data hindered the mosaicking (image stitching) process; the software could not find a tie point to connect the overlapping thermal images. The larger inter quantile range (~5 to 10 °C) of the temperature of the ground from the thermal imageries under plant cover scenarios (Table 3) indicates a high variability of temperature across the field that helped for the visualization of the tile lines.

The effect of rainfall on thermal mapping is inconclusive at this time. Based on the available data, it is tough to conclude that rainfall helped delineate the tile lines. However, comparing the two thermal imageries collected on the 29 July 2019 and 30 July 2019 (Figure 6b,c respectively), 16.8 mm rained in the morning of the 30th which is wetter than the 29th where rainfall occurred two days before (Table 2), the thermal image collected on the 30th has better contrast than the imagery collected on the 29th. The rainfall, which affects moisture viability in the soil, has an effect on the soil thermal property along with other factors including plant cover, plant height and air temperature.

The effect of crop maturity was assessed by comparing images collected at various stages. The development of soybean plant was not uniform across the farm field. where the soybean plants grow taller along the tile lines. More distinct linear pattern was observed at later stage of the soybean plant (Figure 9). Comparing optical images from 15 July 2019 (early growth stage, Figure 9a) with 6 August 2019 (later stage, Figure 9b), both showed preferential growth parallel to the tile lines, however, the distinct tile signature is observed on the image from 6 August 2019. This interpretation is restricted to areas where there are
observable patterns of the tile lines. For example, in the lower left part of the study site (Figure 5c), dense soybean plants show less patterns of the tile lines. This could be due to uniform development of the soybean plants in this part of the study site.

Figure 8. (a) Non-mosaiced thermal images, date collected: 30 July 2019 (b) mosaiced thermal images, collected on 30 July 2019 and (c) not mosaiced thermal images from 24 October 2019 (note: difficulty mosaicking the images collected on this date due to large temperature variability).

Figure 9. (a) Showing optical image collected on 15 July 2019 (b) optical image collected on 6 August 2019. White arrows indicating the location of tile lines.

6. Conclusions

This study explored the feasibility of mapping tile drainage in agricultural fields using UAS mounted radiometric thermal and optical sensors. Multiple flights were conducted to collect data from a site with an existing tile drainage location map. The flight planning integrated weather conditions and land cover, including bare soil and different growing stage of soybean plant.

We found that various maps such as thermal, DSMs and orthomosaics from multiple sensors provided the tile lines signature in most of the study site. No signature of the tile lines was observed when the land surface was bare soil. This does not mean that there must be a plant cover on the land surface, so this technique has to work. Further research is needed to verify this hypothesis, specifically in warm late spring before planting season.

The mapping performance of the UAS methods varies across the field; clear patch lines representing the tile lines were observed in some parts of the study site while less conspicuous in other parts. Generally, the mapping is clear in the eastern part compared to the western part of the study site. This could be due to factors such as topography and
plant development. The western part of the area is relatively elevated and has a higher slope than the eastern part. This permits more runoff than infiltration compared with the lower elevated and flat part of the study site (eastern part). As a result, the soil can quickly dry and become homogeneous in terms of thermal signature. Due to the homogeneity of the thermal imageries, we have had difficulty stitching the images.

Further, considering the effect of plant development, it was very helpful in parts of the study site because there are clear patterns of preferential growth of the soybeans plant parallel to the tile lines. In other areas, where soybean plant growth was uniform, fewer tile line signatures were observed. The study demonstrated that UAS based thermal and optical sensors could be combined to produce map of tile lines. Further refinement of the technique would allow a better and cost-effective mapping of tile drainage.

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