Subsurface tile drained area detection using GIS and remote sensing in an agricultural watershed

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ABSTRACT

Subsurface tile drainage has been used around the globe to lower the water table and drain soils that are seasonally or perennially wet making them suitable for agriculture and/or increasing productivity. However, tile drainage systems have a negative impact on water quality of adjacent streams and ditches due to the transport of excess fertilizer nutrients like nitrogen (N) and phosphorus (P) from fields. To support nutrient management and conservation practices like drain water management (DWM), accurate delineation of the agricultural area drained by tiles is critical for quantifying nutrient yields (nutrient mass per area per time) to downstream water bodies. In this study, we tested Geographic Information System decision tree classification (GIS DTC) and satellite remote sensing based methods (i.e., image differencing) to determine tile drainage area in an agricultural watershed, Shatto Ditch Watershed (SDW) in Indiana, USA. Using these techniques, we estimated that 79% of the cultivated area of SDW is tile drained with 94% accuracy according to the image differencing approach whereas 55% is classified as tile drained with an accuracy of 75% based on estimates from the DTC approach with the most relaxed rule thresholds (where tiles exist on ≤4% slope with poorly and moderately well drained soils). Using satellite imagery to characterize tile drained area at a high resolution over large geographical extent shows promise and will be important for accurately quantifying nutrient yields from tiles which will inform management and conservation efforts to reduce excess nutrient export to downstream water bodies.

1. Introduction

Agricultural watersheds have been modified by artificial tile drainage systems in Europe, North America, Australia, New Zealand and Asia to increase agricultural production (MacEwan et al., 1992; Abbot and Leeds-Harrison, 1998; Monaghan et al., 2002; Blann et al., 2009; Skaggs et al., 2012). Combined with the increased availability of synthetic fertilizers tile drainage has increased cropland productivity resulting in positive impacts on the regional economy and the expansion of agricultural exports (Fausey et al., 1995; Eidman, 1997). However, they have also contributed to changes in surface water quality that have had an impact far beyond farm fields (Cooper, 1993; Goolsby and Battaglin, 2001; Alexander et al., 2008; Blann et al., 2009). Tile drainage systems physically link agricultural fields to surface waters where excess inorganic nitrogen (N) and phosphorus (P) can be rapidly transported to streams (Royer et al., 2004; Vidon et al., 2012; King et al., 2015). Dissolved nutrients are exported downstream and lead to serious environmental problems including algal blooms and hypoxic zones in the Great Lakes (Rockwell et al., 2005; Michalak et al., 2013), Gulf of Mexico (Turner and Rabalais, 2003), Baltic Sea (Conley et al., 2002), Black Sea (Diaz, 2001), Lake Winnipeg (Schindler et al., 2012) and throughout Europe and the United Kingdom (Haygarth et al., 2000; Heathwaite and Dils, 2000) which have negative impacts on drinking water quality, tourism, fisheries, and biodiversity.

The configuration of subsurface tile drainage networks and the area drained by specific tile outlets are often unknown because installation information is either lacking or has been lost over several decades of farming, particularly for tiles installed more than 50 years ago (Blann et al., 2009). It is particularly important to delineate the field area drained by particular tiles in order to accurately quantify nutrient yields (i.e., mass per time per area) contributed to adjacent waterway, especially for attribution of nutrient management or conservation practices (Mitsch et al., 2001; Muenich et al., 2016). One such agricultural conservation practice is drainage water management (DWM), or controlled drainage. It is an example of ecological engineering of agroecosystems by artificially adjusting tile outlet elevations in order to reduce tile flow during certain...
parts of the year such as winter months (Skaggs et al., 2012; Ross et al., 2016). Studies conducted in the US (Cooper et al., 1991; Cooke and Verma, 2012; Williams et al., 2015), Ontario Canada (Gaynor et al., 2002; Drury et al., 2009), Sweden (Weststrom and Messing, 2007) and Egypt (Wahba et al., 2001) have shown reduced losses of nutrients in drainage waters with the adoption of DWNS.

Identifying tile drain networks using field-based methods such as ground-penetrating radar and/or manual tile probing are labor intensive, making them impractical for use at larger spatial scales (e.g., entire watersheds). Alternatively, airborne remote sensing and Geographic Information System (GIS) based methods are quick and provide the potential for spatially-expansive estimates. At present, these approaches have been used to delineate tile drain networks at field scales (Thompson, 2010; Roy, 2013; Reynolds, 2014) and to determine tile drain area over larger scales in the Midwestern U.S. (Sugg, 2007; Naz et al., 2009).

Delineating tile drain networks requires remote sensing data with high spatial resolution that identifies the moisture content of soils based on their relative drying rates immediately after a sufficient rainfall (Verma et al., 1996; Varner et al., 2002; Naz and Bowling, 2008; Naz et al., 2009). However, this approach requires either the acquisition of imagery on demand or access to an archival collection of high spatial resolution images, both of which are expensive options. Alternatively, if the goal is to determine tile drained area instead of mapping actual tile lines, the use of i) satellite remote sensing, and ii) GIS techniques is plausible even at large spatial scales (Sugg, 2007). With regards to satellite remote sensing, Thayn et al. (2011) proposed using readily-available Landsat imagery as an alternative method to characterize tile drained area. Since Landsat data are collected every 16 days over the Earth, it is likely that an image will coincide with a rainfall event (≥2.5 cm). In addition, this approach has the potential of mapping tile drained area at increased spatial resolution (30 m) over a large geographical extent.

In contrast, GIS based analyses use a decision tree to answer a series of yes or no questions, resulting in determination of areas that meet certain criteria. Mostly, these criteria are based on land cover, surface slope and soil drainage class (Sugg, 2007; Naz and Bowling, 2008). Despite a great need to accurately map tile drainage area, we are not aware of any study that has compared both the GIS and satellite remote sensing based methods for determining area of subsurface tile drains. Furthermore, very few field-scale studies have assessed the accuracy of tile drain area delineation using validation techniques (but see Naz and Bowling, 2008). The objectives of our study are to i) compare tile drained area estimation using both GIS and satellite remote sensing techniques, and ii) assess accuracy of the results with information from field observations in an agricultural watershed in Indiana.

2. Materials and methods

2.1. Study area

The study was conducted in the Shatto Ditch Watershed (SDW) located in north-central Indiana (Fig. 1); the SDW drains 1135 ha (3300 acres), and is a tributary of the Tippecanoe River. The 8 km Shatto Ditch is a first-order stream with median discharge of 0.116 m³ s⁻¹ and flashy hydrograph (range = 10–2000 L s⁻¹) typical of other agricultural streams in the Midwest (Royer et al., 2004).

Selected conservation practices, such as the two-stage ditch have been implemented in SDW to reduce nutrient and sediment runoff since 2007 (Roley et al., 2012). Soils are diverse ranging from very organic muck to loam to sandy loam and the majority of SDW is used for corn and soybean cultivation within about 60 agriculture fields. Between 2011 and 2015, the area used for soy cultivation ranged from 286 to 455 ha (30% of the total watershed area) and from 544 to 747 ha (47% of the total watershed area) for corn cultivation (USDA, 2015).

2.2. Tile drain area delineation

We employed two different methods: 1. Decision tree classification (DTC), and 2. Image differentiating to delineate potentially tile drained area in SDW (Naz and Bowling, 2008; Thayn et al., 2011). We used the ArcGIS and ENVI software to perform the analyses of the methods. The DTC approach delineates potential tile drainage area based on certain criteria of land cover, soil drainage class and surface slope, which is accomplished by overlaying spatial layers in a GIS environment. As such, an area that has agriculture as land cover type, poorly drained soils and low slope is assumed to be tile drained (Naz et al., 2009). We used DTC to delineate tile area in SDW and specifically classified tile drainage on any land area with: i) Surface slope ≤ 2%, ii) All poorly drained soil classes including very poorly, poorly, and somewhat poorly drained soils (this classification is based on the SSURGO soil drainage class classification scheme, USDA, 2017), and iii) Corn or soybean cover type. We tested different thresholds in the decision to understand the influence of these criteria on the results. Specifically, we tested the threshold of surface slope ≤ 2% and ≤ 4% and considered moderately well drained soils in addition to poorly drained soils. We generated binary masks of each rule and intersected these masks to generate the final classified images, and the areas where all these conditions were met were classified as “potentially tile drained”. For DTC, we obtained land cover data from the National Agricultural Statistics Service (NASS), soil drainage class information from the Soil Survey Geographic Database (SSURGO), and a 1-m resolution DEM from the Open Topography website (OpenTopography, 2016). We converted all layers to raster format and same resolution (i.e., 30 m) and calculated surface slope from the DEM.

We performed the image differentiating approach using satellite remote sensing data. Surface reflectance and soil moisture are inversely related; therefore, following a rain event, soil over tile drained areas dries relatively faster and has higher reflectance compared to soil over undrained areas (Verma et al., 1996). The shortwave infrared (SWIR) reflectance is strongly related to soil moisture and the difference in SWIR reflectance between a dry versus wet image highlights potential tile drained areas (Thayn et al., 2011).

We first analyzed rainfall data from the nearest meteorological station to the SDW to identify dates when ~2.5 cm rainfall events occurred, and then located optimal images (i.e., cloud-free conditions, bare soil) before and after this time. This amount of rainfall has been proposed and used as a threshold in tile drain detection studies previously (Verma et al., 1996; Northcotte et al., 2000; Varner et al., 2002). We then acquired Landsat 8 images representing dry and wet conditions for dates before and after a 2.3 cm rainfall event on April 20, 2015; the images were captured on April 5 (path and row numbers of 21 and 32, respectively) and April 28, 2015 (path and row numbers of 22 and 31, respectively). The Landsat 8 satellite follows a sun-synchronous orbit, meaning that it passes over any given point on Earth’s surface at the same local solar time. We note the April 28 image had some clouds over the watershed area; therefore, we generated a cloud mask by manually delineating the clouds and their shadows utilizing the near infrared (NIR) false color composite image and multispectral cirrus (1.36–1.38 μm) and thermal (10.60–11.19 μm) bands approximately covering 15% of the total watershed area. Cirrus clouds appear bright while most land surfaces appear dark in the cirrus band of Landsat 8. In the thermal band, clouds and their shadows appear dark since they are cooler. Initially, the masked areas had no data in them. We interpolated these areas by using focal statistics where we took
average of the neighboring pixels using a 5 by 5 pixel moving window successively until all pixels in the masked regions were filled. We then subtracted the SWIR reflectance (1.57–1.65 μm) of the wet image from the dry image to delineate potentially tile-drained areas. In the difference image, tile-drained areas appear lighter and non-tile-drained areas appear darker as reflectance in SWIR is inversely related to soil moisture. Areas that were dry but remained wet after the rain event (i.e., non-tile-drained) appeared lighter in color, while areas that were dry before and quickly dried after the rain event (i.e., tile-drained) appeared darker. We used a threshold value of less than or equal to zero in the difference image to classify the watershed as tile drained versus non-tile drained. For both approaches, we assumed tile drainage only occurred on currently cultivated corn and soybean areas of the SDW. The difference image was masked by the soybean and corn cover mask generated using the DTC approach. We also considered the combination of the two approaches for tile drained area estimation. We took the intersection and union of the two approaches to determine the minimum and maximum extent (%) of tile drained area of the watershed.

2.3. Accuracy assessment (Validation)

We used multiple sources of data for validation. First, we acquired the geographic coordinates of all the tile drain outlets draining into Shatto Ditch using a hand-held GPS. Second, we collected spatial data indicating subsurface tile drain location in several fields in 2015 and 2016. We also acquired the spatial data layers of tile drain locations within SDW that were installed by the county surveyor in Kosciusko Co. Lastly, we gathered information on the presence of tile drains in the fields within SDW based on personal communication with farmers.

We employed two types of validation to assess the accuracy of tile drain area estimation (Fig. 2). First, we used a quantitative approach limited to two fields for which we had collected tile drain
location data. We overlaid the tile drain location points on the DTC and image differencing results, and then we counted the number of points corresponding to potential tile drained areas, dividing the points within tile drained areas by the total number of points and reporting the results as percent values. The second method of validation was a qualitative method in which we assumed all the fields to be tile drained that we knew had tile drains installed but we did not have information on the exact location of those tile drains. We computed the number of potentially tile drained pixels estimated according to each method and then divided this by the total number of pixels of all fields.

### 3. Results and discussion

#### 3.1. Decision tree classification

We obtained different results based on various threshold criteria used in the DTC approach. Approximately 38% of the cultivated area of the watershed was classified as tile drained when a 2% slope threshold and only poorly drained soils were used (Fig. 3a, Table 1). When we included moderately well-drained soil class without changing slope threshold, 42% of the watershed was classified as tile drained (Fig. 3b, Table 1). When we increased the slope threshold to 4% by only considering poorly drained soils, tile drained area estimated by the DTC approach increased to 50% (Fig. 3c, Table 1). Finally, we estimated 54% of the watershed to be tile drained with the most liberal threshold rules including 4% slope and poorly and moderately well drained soils (Fig. 3d, Table 1). Relaxing the slope threshold resulted in a greater increase in the area classified as tile drained (29% and 32%) compared to relaxing soil drainage class thresholds (8% and 11%) for a given soil drainage category and surface slope, respectively. The quantitative accuracy of tile drained area characterization ranged from 58% to 75% for the DTC approach with different threshold values and relaxing the soil drainage class threshold for a given surface slope improved the quantitative accuracy more compared to relaxing the slope threshold for a given soil drainage category (Table 1). Qualitative accuracy ranged from 37% to 51% for DTC with different slope threshold values (Table 1). Addi-

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<td>58</td>
<td>37</td>
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<tr>
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<td>DTC slope ≤ 4% and poorly and moderately well drained soils</td>
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<td>Intersection of DTC and Image Differencing</td>
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<td>Union of DTC and Image Differencing</td>
<td>86</td>
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Fig. 3. Tile drained area characterization of Shatto Ditch Watershed according to DTC approach. Combination of different thresholds of tile drain occurrence were tested on: (a) ≤2% slope on poorly drained soils with soybean and corn, (b) ≤2% slope on poorly and moderately well drained soils with soybean and corn, (c) ≤4% slope on poorly drained soils with soybean and corn, and (d) ≤4% slope on poorly and moderately well drained soils with soybean and corn.

3.2. Image differencing

We estimated that 79% of corn and soybean cultivated area of the SDW is tile drained according to the image differencing approach with an accuracy of 94% and 78% based on quantitative and qualitative validations, respectively (Fig. 5, Table 1). This approach and resulting image also represents the natural orientation patterns of the fields more realistically, with fields having rectilinear patterns in homogenous color appearances, which can be seen clearly when viewing how lighter or darker areas are positioned in the parcels (Fig. 5a). There are a few fields which do not appear to be tile drained based on the image differencing approach, but are classified as being tile drained using the DTC approach. For example, the bright, white section in the northern part of the watershed (Fig. 5a, Table 1) is not tile drained according to the image differencing approach due to an artifact of cloud presence. Even after cloud amelioration using focal statistics, that region remained difficult to correct. Overall, the image differencing approach resulted in a more homogenous characterization of tile drained area and a larger amount of tile drained area estimation compared to DTC. Image differencing approach also characterized the tile drained area more accurately by aligning with the county tile drains, the GPS points, and known tile drained fields (Figs. 5b–d).
3.3. Comparison of image differencing versus DTC for predicting tile drainage area

The DTC and image differencing methods yielded contrasting results. The DTC approach resulted in a patchier characterization of tile drained area and the area estimated to be tile drained was lower compared to image differencing approach. The criterion used in the DTC approach, particularly soil drainage class was the major factor causing the patchy tile drained area characterization due to its high spatial variation across the watershed. Additionally, the rules
employing the DTC process affected the drainage area estimations. We acknowledge that these rules were somewhat arbitrary and did not necessarily reflect the ground practices by the farmers. For example, setting the slope threshold to ≤4% increased the area that was potentially tile drained from 38% (with a ≤2% threshold) to 50%. Considering only poorly drained soils also resulted in an underestimation of tile drained area because some tile installations are deployed irrespective of drainage class to improve yield (B. Romine, personal communication), at least based on our field observations. Again, we acknowledge that this may not be the case in every watershed but should be kept in mind when conducting tile drain estimation studies.

We also found that the image differencing approach was better at reflecting the actual tile drained area in the SDW. Instead of using
pre-determined set of rules, this method is based on a more physical reasoning (i.e., moisture content of the soil and relative drying rate after a rainfall). As such, we expect it to provide a more realistic output compared to DTC. However, the accuracy of the estimation of tile drained area by the image differencing method relies on the acquisition of an image i) free of cloud cover, ii) without crop cover, iii) during dry conditions before and wet conditions shortly after, iv) a minimum rainfall amount of approximately 2.5 cm. These bounded conditions make image acquisition challenging. Landsat data, with a 16-day recurrence interval, combined with the prevalence of cloud cover around rainfall events, make obtaining these images an ongoing challenge. In our analysis, we optimized our image selection by accounting for these factors by making sure there was enough rainfall before image acquisition, minimal cloud cover and maximum bare soil cover. Additionally, the threshold value (e.g., ≤0) selected in the difference image to classify the landscape as tile drained and non-tile drained also affected the outcome. The most straightforward approach was to select a threshold value of ≤0 since areas that return to dry conditions quickly after rainfall (e.g., those that are tile drained) will have higher reflectance and the difference between them will be low. On the other hand, the reflectance over an area with wet conditions after a rainfall (e.g., non-tile drained) will be low and the difference compared to the dry conditions will be greater.

We reiterate the ongoing need for validation information on tile drain presence whenever possible (Sugg, 2007) to assist in accurately delineating watershed area given the prevalence of subsurface tile drains. The image differencing approach using satellite imagery allows for the characterization of tile drained area at a high resolution over large spatial extent compared to previous studies conducted by the USDA (1992) and the World Resources Institute (WRI) (Sugg, 2007). Nevertheless, cloud-free images representing dry and wet conditions around a rainfall event must be available.

3.4. Combination of DTC and image differencing methods

We found that 30% of area under row-crop cultivation in SDW was characterized as tile drained when the intersection of the DTC and image differencing methods was considered while 86% of the area was characterized as tile drained when the two methods were combined (Fig. 6, Table 1). The intersection of the two methods had an accuracy of 53% and 31% using quantitative and qualitative validation, respectively (Table 1). We also discovered that union of the two methods predicts the largest tile drained area with the highest accuracy, i.e., 96% and 87% using quantitative and qualitative validation, respectively (Fig. 6b, Table 1). In conclusion, when the position and frequency of tile drain outlets and known tile drained fields are considered, union of the two methods characterizes tile drained area with the most accuracy (Fig. 6b).

Certain regions of the watershed appear to be potentially tile drained according to the DTC and image differencing methods (Fig. 6a). We are confident that these fields are tile drained, which is also supported by the presence of tile outlets into the ditch adjacent to these fields. Also, two of the fields for which we have actual tile drain network location information supports our estimates based on the intersection of the DTC and image differencing methods. However, we know that most of the cultivated fields are tile drained in the watershed so the estimate based on the intersection of the two methods likely underestimated the actual tile drained area.
3.5. Comparison of DTC and image differencing to other studies

Our results provided higher estimates of tile drained area than previous studies conducted at larger spatial extents that encompassed the SDW. For example, approximately 13% of the SDW area was classified as tile drained according to the 1992 National Resource Inventory survey, while the estimate increased to 22% in a more recent survey by WRI that attempted to improve the NRI estimates by integrating GIS data (Sugg, 2007). Most recently, 25% of the county was estimated to be tile drained according to USDA NASS Census of Agriculture conducted in 2012 (USDA, 2012). However, these last two estimates were conducted at the county level, which is a larger spatial extent than for just the SDW. In west-central Indiana, Naz et al. (2009) determined that 79% of the Hoagland watershed (20,200 ha) was potentially tile drained using the DTC method. These authors also reported that their tile drained area prediction for the watershed using high resolution aerial imagery was 50% and showed a closer agreement to previous studies (Sugg, 2007; Sui, 2007), suggesting that the DTC method overestimated tile drain area due to the assumption that all poorly drained soils are tile drained. However, we note that this study did not use any validation techniques. Our results differed from these findings in that even with the most relaxed threshold rules (i.e., ≤4% slope on poorly and moderately well drained soils), DTC estimated that the tile drained area was 38%, which was 25% less than that predicted by the image differencing method in our study, in addition to having had lower accuracy. Furthermore, we also have field observations that confirm that subsurface tile lines are not limited to installation in only poorly drained soils. The decision to install tile drain is a complex decision-making process, which also depends on factors such as the presence of surface drainage, knowledge and preference of farmers about subsurface drainage, cost-benefit analysis and previous extent of tile lines (Sugg, 2007; Naz et al., 2009).

4. Conclusions

We compared two different methods (i.e., DTC and image differencing) for delineating tile drained area in an agricultural watershed in northern Indiana. The image differencing approach using satellite imagery yielded a more realistic and accurate classification of tile drained area in the watershed compared to the DTC approach. Overall, 79% of the area in row crop cultivation in the SDW was estimated to be tile drained with 94% accuracy according to the image differencing approach whereas 54% was classified as tile drained with an accuracy of 75% based on the DTC approach with the most relaxed thresholds rules. In this study, the union of DTC and image differencing methods estimated the largest tile drained area (86%) with the highest accuracy (96%). We found that it is critical to obtain cloud free images that are representative of dry and wet conditions around a rainfall event in order for the image differencing approach to be effective. It is also necessary to ground truth with tile drain installation information in order to assess the accuracy of results and decide on threshold values to be used for both approaches. Using satellite imagery paves the way for characterizing tile drained area at a high resolution over large spatial extent. This will be useful to assess the effectiveness of ecological engineering practices aimed at conservation like DWM at the landscape level since nutrient yields (i.e., mass per time per area) attributable to tile drains can only be estimated if the tile drained area is known.

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